# Driving the Future with AI: Advancing Ontario's Mobility Ecosystem

Assessing applications, enabling conditions, and opportunities for Ontario's mobility future

Quarterly Specialized Report Draft

Ontario Vehicle Innovation Network

June 2026

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# Executive Summary

Artificial intelligence (AI) is rapidly transforming the global automotive and mobility sector, shaping how vehicles are designed, operated, and connected within broader transportation systems. From advanced driver assistance systems and autonomous driving to predictive maintenance, fleet optimization, and smart mobility solutions, AI is becoming a foundational technology across the mobility value chain. As global adoption advances, jurisdictions are competing to capture economic value, develop specialized capabilities, and position themselves within emerging AI-enabled mobility ecosystems.

AI applications in the automotive and mobility sector are expanding across several key domains. In vehicles, AI is enabling advanced perception, decision-making, and control systems that underpin autonomous and assisted driving capabilities. In manufacturing, AI is supporting quality control, predictive maintenance, and process optimization. Across mobility systems, AI is driving improvements in traffic management, route optimization, logistics coordination, and fleet operations. These applications are increasingly integrated, reflecting a shift toward connected, data-driven mobility ecosystems rather than standalone technologies.

Despite this progress, the adoption of AI in mobility remains uneven and is often concentrated in specific use cases where clear operational value can be demonstrated. Autonomous driving continues to face technical, safety, and regulatory challenges, particularly in complex and unpredictable environments. At the same time, more near-term applications, such as fleet optimization, predictive maintenance, and driver assistance systems, are advancing more quickly due to their clearer return on investment and lower deployment risk. Stakeholders consistently emphasized that AI adoption is not a single pathway but varies significantly depending on use case, data availability, and system integration requirements.

Ontario has a strong foundation to participate in the growing AI-driven mobility ecosystem. The province benefits from a globally recognized AI research base, a large automotive and parts manufacturing sector, and established capabilities in software, sensing technologies, and systems integration. Ontario's dense network of academic institutions, startups, and multinational firms contributes to a robust pipeline of AI talent and innovation. In addition, the Ontario Vehicle Innovation Network (OVIN) Regional Technology Development Sites and innovation programming provide critical infrastructure for testing, validation, and demonstration of AI-enabled mobility technologies.

Several challenges continue to shape the pace and scale of AI deployment. Access to high-quality, real-world data remains a key constraint, particularly for training and validating AI models in safety-critical applications such as autonomous driving. Integration across vehicles, infrastructure, and digital systems introduces complexity, requiring coordination across multiple stakeholders and standards. Talent availability, particularly in specialized AI and software roles, remains competitive globally. Regulatory clarity, especially in areas such as autonomous systems, safety assurance, and data governance, is also a critical factor influencing investment decisions.

In this environment, strategic focus will be essential to enable Ontario to capture value from AI in mobility. Opportunities are most prominent in areas where the province already has strengths, including advanced manufacturing, applied AI research, and system integration. Near-term opportunities are concentrated in commercially viable applications such as fleet management, logistics optimization, and advanced driver assistance systems. Longer-term opportunities include autonomous vehicle development, connected infrastructure, and integrated mobility systems, which will require sustained investment, regulatory alignment, and ecosystem coordination. Taken together, AI represents a critical enabler of the future mobility system. While adoption will occur at different speeds across use cases, a targeted, ecosystem-based approach can enable Ontario to build long-term competitive advantage in AI-

enabled automotive and mobility innovation.

In this context, OVIN plays a central role in advancing Ontario's leadership in automotive and mobility innovation. Through its focus on research and development, testing and validation, and industry collaboration, OVIN supports the commercialization of emerging technologies, including AI-driven solutions. It is well positioned to accelerate this transition by de-risking emerging technologies through pilot projects, enabling collaboration across industry and academia, and strengthening pathways from innovation to commercialization. By aligning investments with high-impact use cases, supporting data and testing infrastructure, and fostering partnerships across the mobility ecosystem, OVIN can play a catalytic role in advancing AI adoption in the sector across the province.

This report builds on OVIN's mandate to strengthen Ontario's position in connected, autonomous, and smart mobility by assessing how AI is shaping the sector and where the province can capture strategic opportunities. It aims to provide a clear view of the current state of AI adoption in the automotive and mobility sector, the key technologies and applications driving change, and the factors shaping deployment in Ontario. It examines how AI is being applied across vehicle systems, infrastructure, and mobility services, and outlines the enabling conditions required to support scale, including data access, talent, infrastructure, and policy frameworks.

# 1. AI as a Transformational Technology

Artificial intelligence (AI) is emerging as a foundational technology transforming the automotive and mobility sector, enabling more connected, automated, and data-driven systems. As AI capabilities advance, organizations are embedding them across vehicle design, manufacturing, and operations to improve performance, efficiency, and safety.

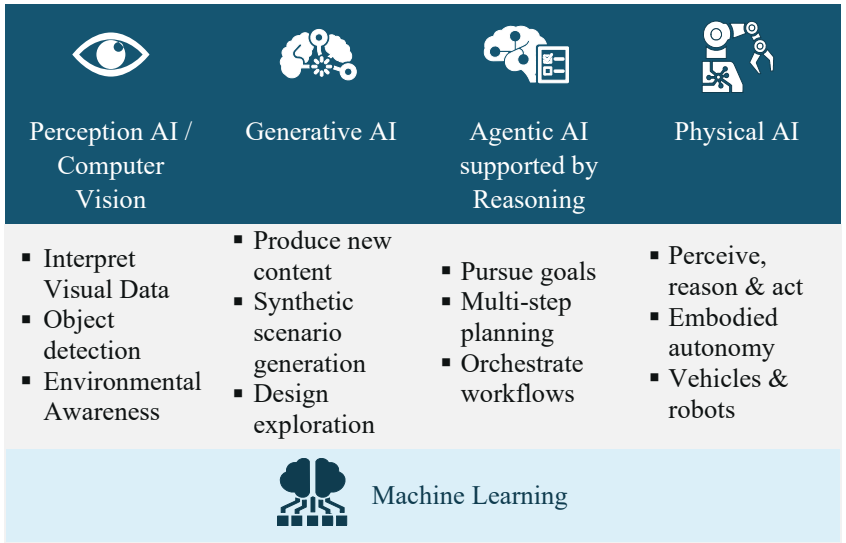
This section introduces the core AI technologies shaping the sector, including machine learning, computer vision, and emerging paradigms such as generative and agentic AI. It outlines the key enablers required for deployment, where AI is delivering the most value today, and the broader considerations influencing adoption across the automotive and mobility ecosystem.

## 1.1 Core AI Technologies Reshaping the Sector

### Overview of AI Technologies Relevant to Mobility

AI has become a major driver of innovation in the automotive and mobility sector. AI comprises a set of technologies that simulates human intelligence to learn, reason, solve problems and perform a variety of tasks such as data analysis and answering questions.[1] This section introduces the core methods that define AI capability in mobility, including machine learning (ML), computer vision (CV), and the related paradigms of perception, generative, agentic, and physical AI, before examining how these capabilities are deployed within vehicle and system architectures.

**Figure 1: AI Capability Spectrum in Automotive and Mobility**




At the core of the AI toolbox is ML, often described as the "learning brain" of an AI system. ML enables computers to learn patterns from data and make predictions or decisions without being explicitly programmed for every scenario. This ability to recognize patterns and improve with experience underpins many modern AI applications.[2] Building on this foundation, AI systems incorporate additional capabilities that allow them to interact with and generate information. CV, a core Perception AI technology, enables machines to interpret visual data such as images and video, supporting tasks such as object detection, lane recognition, and environmental awareness.[3] These systems rely on ML methods to extract meaning from pixel-level inputs and translate them into actionable insights.

Generative AI extends these capabilities by producing new content rather than only interpreting existing inputs. This includes applications such as design exploration, synthetic data generation, code development, and scenario creation, where models learn from existing datasets to generate new patterns and solutions.[4] Agentic AI takes this a step further from producing outputs to pursuing goals. Agentic systems plan multi-step processes, initiate actions, adapt to changing conditions, and coordinate across tools and systems with minimal human intervention. This means that AI is no longer confined to a single function but can orchestrate end-to-end workflows.[5] Physical AI combines these AI capabilities with sensors, actuators, and control systems so that intelligence can perceive, reason, and act directly in the physical world, including within vehicles, robots, and industrial equipment. Jensen Huang, CEO of NVIDIA, describes this shift as the "next wave" of AI, where advances in perception, generative, and reasoning systems are translated into embodied autonomy across real-world machines and environments.[6]

In mobility applications, these capabilities are rarely used in isolation. Vehicles and mobility systems must process multiple streams of information at the same time, which has led to the increasing use of multimodal AI. Multimodal systems combine inputs such as camera images, radar signals, global positioning system (GPS) data, and user interactions to build a more complete understanding of the operating environment.[7] This differs from single-modality systems, which rely on one type of input, such as audio or visual data alone. By integrating

multiple data sources, multimodal systems allow each input to support and validate the others. For example, in autonomous vehicle applications, camera data, radar signals, and location information are analyzed together to interpret surroundings before ML models determine an appropriate response.[8] If one data source becomes unreliable, such as reduced camera visibility due to weather conditions, other inputs can help maintain system performance. This improves the robustness and reliability of AI systems in real-world operating conditions.

These deployment approaches shape how AI delivers value across the automotive and mobility sector. As AI capabilities are embedded into vehicle design, manufacturing, and operations, they influence outcomes across productivity, safety, system performance, and the business models. Beyond vehicle and industrial applications, AI is also being applied at the municipal and urban level to improve traffic management, enhance safety for pedestrians and cyclists, and support more predictive and responsive mobility systems. Table 1 summarizes four core value drivers across the vehicle lifecycle and mobility ecosystem.

A separate but equally important dimension of AI in mobility relates to how these systems are deployed. The effectiveness of AI depends not only on model capability, but also on where and how those models operate within the system. In mobility applications, this distinction is most often described through edge and cloud deployment models. Cloud-based AI supports large-scale data processing, model training, and system-wide coordination. It enables aggregation of data across fleets, continuous model improvement, and centralized management of software and services.[9] Edge AI, in contrast, refers to models that run directly on vehicles or devices, enabling real-time processing and immediate decision-making. For commercial applications, this is critical for safety-related functions such as braking, steering adjustments, and collision avoidance, where delays are not acceptable. In defence contexts, it is also about maintaining control when

**Table 1: Core AI Value Drivers**

| Productivity & Efficiency | Safety & Risk Mitigation |
|---|---|
| AI improves productivity and efficiency by enabling organizations to deliver more output with fewer inputs. This reduces cost, waste, and downtime across design, manufacturing, and operations. AI can shorten development cycles through simulation and digital testing, while improving day-to-day performance through predictive maintenance, vision-based quality control, and optimized inventory, logistics, routing, and traffic flows. | AI strengthens safety and risk mitigation by identifying hazards and defects earlier and more consistently. This reduces the likelihood of incidents and lowers warranty and liability exposure. In manufacturing environments, this often involves anomaly and defect detection systems that trigger timely alerts and operator intervention. In vehicles and fleets, it includes advanced driver assistance systems (ADAS) such as automatic emergency braking and lane assist. |
| **Automation & Scalability** | **New Business Models (SDV / Services)** |
| AI enables automation and scalability by shifting routine and repetitive tasks from people to systems that can operate continuously and consistently. This allows organizations to scale output without proportional increases in labour. In manufacturing, this includes the use of robotics, automated guided vehicles, and real-time scheduling and throughput optimization. In mobility services, AI supports improved dispatching, routing, pooling, and early autonomy deployments that increase asset utilization over time. | AI supports new business models by making vehicles and mobility services increasingly software-driven and continuously upgradable. This shifts revenue models from one-time transactions toward recurring and service-based streams. For original equipment manufacturers (OEMs), this includes subscription-based features delivered through secure software update pipelines. For mobility operators, it enables models such as mobility-as-a-service subscriptions, usage-based insurance, and personalized in-vehicle experiences. |

communication links are degraded or under active attack. Thus, edge AI techniques are increasingly deployed on unmanned systems such as drones and loitering munitions, where onboard processing supports real-time target recognition and guidance even in contested or disconnected environments.[10] By operating locally, edge systems reduce reliance on continuous connectivity and allow vehicles and devices to function reliably in environments with limited network coverage.[11]

## 1.2 The Foundational Enablers for AI Deployment

While AI technologies define what is technically possible in the automotive and mobility sector, their successful deployment depends on a set of underlying enabling conditions. These enablers determine whether AI can move beyond isolated pilots into scalable, reliable, and safety-critical applications across vehicles, infrastructure, and mobility systems. Without these foundational elements, even advanced AI solutions remain constrained in performance, reliability, and adoption.

### Robust Technological Infrastructure

AI systems in mobility require high-speed connectivity, large-scale computational capacity, data storage, and reliable energy supply. As AI adoption accelerates, existing infrastructure is increasingly insufficient.[12] Modern vehicles depend on continuous, high-bandwidth communication through 5G cellular networks and vehicle-to-everything (V2X) technologies. These systems enable real-time data exchange between vehicles, cloud platforms, and surrounding infrastructure, supporting functions such as over-the-air (OTA) updates, live navigation, and coordinated fleet operations. In safety-critical applications, connectivity must deliver latency as low as 1 millisecond and reliability approaching 99.999 percent uptime to ensure that systems can respond predictably in real-time.[13]

**Over-The-Air (OTA) Update in Automotive**

OTA updates allow software, firmware, and sometimes AI models to be remotely updated in vehicles after they are deployed. In the automotive context, OTA updates enable bug fixes, feature enhancements, and safety improvements without requiring physical recalls.

At the same time, compute requirements are increasing rapidly. AI models rely on high-performance computing environments using GPUs (Graphics Processing Units), specialized AI chips, and large-scale cloud infrastructure. Within vehicles, the shift toward software-defined architectures is driving consolidation from distributed electronic control units to centralized high-performance computers. These systems process sensor data from cameras, radar, and LiDAR (Light Detection and Ranging) in real-time, enabling perception, decision-making, and control functions required for advanced driver assistance and autonomous systems.[14]

Energy infrastructure is an equally critical element. AI requirements are driving significant increases in power demand, particularly in data centres. In the United States, electricity demand from AI-focused data centres is projected to grow from approximately 4 gigawatts in 2024 to 123 gigawatts by 2035, representing a more than 30 times increase. This growth highlights the need for grid expansion, energy efficiency improvements, and integration with renewable energy systems.[15] Digital infrastructure also enables development and validation. Simulation platforms and digital twins allow AI systems to be tested under a wide range of scenarios before deployment.[16] These environments provide scalable testing and validation capacity, which is particularly important for safety-critical mobility applications.

### Data Readiness and Data Sovereignty

Data is a core input to AI systems, but the focus has shifted from volume to quality. The industry is moving from “big data” toward “smart data”, emphasizing datasets that are accurate, well-labeled, diverse, and contextually relevant.[17] This shift reflects the need for AI systems to operate reliably in complex, real-world environments where incomplete or inconsistent data can directly affect outcomes.

The value of smart data is illustrated by Transport for London's (TfL) network-wide traffic optimization initiative, which forms part of its five-year congestion strategy. Central to this approach is the enhancement of the Yutraffic Fusion traffic control system, which integrates and standardizes data from across London's road network to inform signal timing decisions. By analysing richer, cleaned, and more contextual datasets, the upgraded system enables AI-supported prediction of traffic patterns and more adaptive signal control. TfL estimates that these improvements could reduce traffic delays by up to 14 percent. The strategy is complemented by the deployment of Direct Vision Standard, AI-enabled monitoring infrastructure, including computer-vision cameras that differentiate between pedestrians, cyclists, wheelchair users, and vehicles. These capabilities allow traffic signals and crossing times to better reflect actual street use, supporting both congestion reduction and improved pedestrian safety across busy intersections, while also contributing to more reliable public transit operations. [18]

Achieving this level of data readiness requires significant effort. Data preparation remains one of the most resource-intensive stages of AI development, with data scientists often spending up to 80 percent of their time cleaning, labeling, and validating datasets.[19] Poor-quality data can introduce bias, degrade model performance, and increase safety risks, particularly in perception and decision-making systems where reliability is critical.

Alongside data quality, data sovereignty has become an increasingly important consideration for AI deployment, particularly in transportation and public-sector applications. Data sovereignty refers to the principle that data is subject to the legal and regulatory frameworks of the jurisdiction in which it is generated or stored.[20] Industry and policy reports note that AI systems increasingly rely on sensitive location, mobility, and behavioral data, making compliance with local data governance, privacy, and cross-border data transfer rules a critical design requirement rather than an afterthought. As governments tighten requirements around data localization and control, transportation agencies and AI developers must design data architectures that balance analytical performance with jurisdictional oversight, accountability, and public trust.[21] Failure to address data sovereignty risks can limit the scalability of AI systems, restrict data sharing across regions, and delay implementation even when technical capabilities are mature.

## Governance, Policy, and Safety Frameworks

AI deployment in mobility is closely tied to governance, given the safety-critical nature of the sector. Policies, regulatory frameworks, and ethical guidelines provide the guardrails required to manage risk while enabling innovation.

Globally, governance approaches are evolving but remain fragmented across jurisdictions. International efforts, such as the United Nations Educational, Scientific and Cultural Organization (UNESCO) global AI ethics framework adopted by 193 countries, establishes common principles related to human rights, fairness, and accountability.[22] At the national level, more than 60 countries have developed AI strategies, with regulatory approaches such as the European Union's AI Act introducing risk-based frameworks for high-impact applications, including autonomous vehicles.[23]

In the automotive sector, organizations such as United Nations Economic Commission for Europe (UNECE) are extending vehicle regulations to address AI-driven systems, including requirements for cybersecurity, system validation, and human-machine interaction. [24] These frameworks build on existing standards such as ISO 26262 and Safety of the Intended Functionality (SOTIF), while introducing new considerations related to explainability, data quality, and lifecycle validation.[25] [26] While Canada does not directly adopt UNECE vehicle regulations, Transport Canada aligns its cybersecurity guidance and policy development with international frameworks. As a result, UNECE requirements increasingly influence Canadian manufacturers and suppliers, particularly those exporting to markets where compliance

with UNECE regulations is mandatory.

Industry practice illustrates how governance frameworks are being applied in real-world deployments. Waymo, for example, worked closely with regulators and public agencies prior to launching its autonomous taxi service. The company conducted extensive validation, including more than 20 billion miles of simulated driving, and shared safety data with regulators to inform emerging standards.[27]

Overall, governance functions as both a constraint and an enabler for AI in mobility. Clear rules, defined responsibilities, and transparent processes provide the regulatory certainty needed to scale AI solutions with confidence. In contrast, uncertainty around liability, explainability, and compliance can delay deployment, increase costs, and slow innovation.

## Human Capital and Organizational Capability

Human capital is a foundational enabler of AI deployment in mobility, as advanced systems cannot be designed, deployed, or governed without the appropriate skills and organizational readiness.

Globally, shortages in AI-related skills remain a key constraint on deployment. Surveys indicate that 65 percent of organizations have abandoned AI initiatives due to insufficient internal capabilities,[28] and that gaps in foundational elements that create an environment that encourages adoption by employees may cause companies to miss up to 40 percent of the potential productivity gains that AI could deliver.[29] At the same time, 95 percent of organizations identify AI skills as a key factor in hiring decisions, reflecting the increasing importance of these skills for workforce readiness.

In the automotive sector, this challenge is particularly pronounced due to the need to integrate software, data, and engineering disciplines. Organizations are responding through internal training programs, partnerships with universities, and targeted hiring strategies. Germany's AI talent programs, for example, have supported thousands of professionals through advanced education and reskilling initiatives, helping align workforce capabilities with the transition toward software-defined vehicles and autonomous systems.[30] These efforts illustrate how sustained investment in human capital enables organizations to translate AI technologies into operational deployment, manage risk, and maintain competitiveness as the mobility sector evolves.

## Multi-Stakeholder Partnerships and Collaboration

AI deployment in mobility requires coordination across a broad ecosystem of stakeholders, including automakers, technology providers, telecommunications companies, regulators, and research institutions.[31] Most organizations do not have the full set of capabilities required to independently develop and scale AI systems. Thus, collaborative models are increasingly used to address shared challenges.

The intent of these collaborations is to pool resources, share data, and establish common standards to address system-level challenges that individual organizations cannot solve independently. The need for this level of coordination is driven by the scale and structure of data generated by modern vehicles. Future connected vehicle services are expected to require on the order of 1 to 2 terabytes of raw data per vehicle per day to support applications such as intelligent driving, real-time mapping, and cloud-assisted services. [32] Existing mobile communication networks and centralized cloud computing systems are not fully optimized to handle these requirements. As a result, there is a need for collaboration across the stakeholders to redesign system architectures and reconsider network deployments to align system design, ensure interoperability, and establish common standards that support global deployment of connected vehicle services.

Large-scale collaborative initiatives further demonstrate the value of this approach. The European Union's L3Pilot project brought together industry and research partners to test automated driving systems across 10 countries with 1,000 drivers, supported by €68 million in funding.[33] The resulting data and insights have informed both regulatory

development and industry standards, accelerating progress toward higher levels of vehicle automation. Multi-stakeholder partnership and collaboration, therefore, could enable cost sharing, reduce duplication, and support the development of interoperable systems that can scale across regions and markets. The foundational enablers discussed above help explain what is required to make AI deployment possible in mobility. The next consideration is whether these systems can be adopted and scaled under the operational realities of the sector.

## 1.3 Adoption Considerations

Mobility AI adoption is shaped by constraints that differ from many other digital domains. Because systems operate in safety-critical environments, organizations face higher assurance burdens and slower scaling dynamics than in typical consumer software. This section highlights key adoption challenges, including safety-critical performance and latency, long asset lifecycles, explainability and liability, and cyber-physical security which are examined below.

### Safety-Critical Performance and Latency

A primary consideration in deploying AI-enabled mobility systems is safety-critical performance and latency. In cars, public transit, and industrial operations, failures are not only costly but can be catastrophic. Unlike a phone app or web service, where faults primarily affect user experience, an AI error in a moving vehicle or on a factory floor can contribute to collisions or injury. This creates low tolerance for errors and stringent requirements for real-time responsiveness. Mobility AI systems must reliably perceive their surroundings and respond within fractions of a second. For example, an autonomous system that is slow to recognize a hazard, or misclassifies an object, can increase the likelihood of an incident that a faster or more accurate system may have avoided. As a result, safety-critical mobility AI requires automotive-grade assurance practices, including rigorous validation and verification, expanded scenario coverage through simulation-based testing, and redundancy across sensors and algorithms.[34] Standards such as ISO 26262 and emerging machine-learning safety frameworks (e.g., ISO/PAS 8800) are increasingly used to structure evidence and controls. Advanced AI features are more likely to scale when they can demonstrate speed, reliability, and fail-safe behaviour under real-world conditions.[25] [35]

### Long Product and Asset Lifecycles

The automotive sector operates on product and asset lifecycles that are significantly longer than those in the technology sector.[36] Digital products such as smartphone applications are updated frequently, and devices are often replaced within a few years. By comparison, vehicle models typically remain in-market for 5 to 8 years and continue operating on the road for a decade or more. The average vehicle in use in the United States is nearly 13 years old[37], while supporting infrastructure such as traffic signals and public transit systems are designed to function for multiple decades.[38]

These extended lifecycles have direct implications for AI deployment in mobility. Systems introduced today must remain functional and relevant over long time horizons, often well beyond the pace of technological change. An AI-enabled vehicle sold today may still be operating into the late 2030s, where it will encounter evolving environments, shifting user behaviours, and changing regulatory requirements. This places sustained demands on system maintainability, software and hardware update strategies, and long-term reliability.

### Explainability, Liability, and Regulatory Accountability

As discussed in Section 1.2, governance can act as both an enabler and a constraint on AI deployment in mobility. While clear rules and oversight mechanisms support trust and scalability, issues related to explainability, liability, and regulatory accountability can constrain adoption. These issues are particularly important in mobility because AI-driven decisions directly affect safety, requiring clarity on how decisions are made and who is responsible when outcomes are adverse. Traditional automotive systems are largely deterministic and traceable,

whereas many AI systems are not. In safety-critical applications, this limited explainability can constrain deployment and reduce public acceptance.[39] At the same time, liability remains unresolved in many jurisdictions, particularly in determining whether responsibility rests with the OEM, the software provider, or the operator.[40]

These challenges have led to increasing regulatory scrutiny. As discussed above, frameworks such as the European Union AI Act and UNECE regulations place growing emphasis on ensuring that automotive AI systems are auditable and trustworthy by design.[41] This has practical implications for system development and deployment. Organizations are expected to maintain decision logs, implement fail-safe mechanisms, and provide evidence of rigorous testing and validation. Explainable AI (XAI) methods are being adopted to support these requirements by enabling stakeholders to interpret system behaviour in specific scenarios. These methods are often complemented by deterministic safety layers that can override unsafe actions, improving transparency and reinforcing system control.[42]

Clear accountability is also closely tied to the business case for mobility AI. As control shifts from human drivers to automated systems, liability increasingly moves toward manufacturers and software providers, with direct implications for insurance structures and risk allocation. Where responsibility is not clearly defined, insurers tend to adopt more conservative positions, resulting in higher coverage requirements and stricter underwriting conditions. This increases deployment costs and can slow adoption.[43] In contrast, systems that demonstrate safety performance and provide defensible explanations of their behaviour may support more efficient regulatory approval and lower risk-related costs.[44] In this context, organizations must address not only whether a system functions as intended, but also whether it can demonstrate safety, explain its decisions, and support clear assignment of responsibility when failures occur. Until these governance questions are addressed, adoption and scale-up in mobility will remain appropriately cautious.

## Cyber-Physical Security Risks

The connectivity, digital infrastructure, and software integration that support AI deployment in mobility also increase exposure to cyber-physical risk. As vehicles become more connected to cloud platforms, infrastructure, and remote update systems, digital vulnerabilities can translate into real-world safety consequences. Cybersecurity therefore becomes a core condition of safe and trustworthy AI deployment. In dual-use mobility systems, where the same connected vehicles and platforms may support both everyday local transport and security or emergency-response operations, cyber-physical weaknesses can have broader operational and public-safety implications.

These risks arise across multiple parts of the connected vehicle ecosystem. Vulnerabilities in telematics systems, connected vehicle platforms, and cloud backends have demonstrated the potential for remote access to vehicle functions at scale, including starting or stopping vehicles, unlocking doors, and disabling access through companion applications.[45] [46] As vehicles become more networked, these types of exposures must be addressed early in both design and deployment. AI-enabled systems introduce additional security concerns because they can be manipulated in ways that affect how the vehicle interprets and responds to its environment. For example, slight changes to road signs or surrounding conditions can cause perception systems to misread critical signals. Unlike traditional vehicles, these vulnerabilities can influence real-world system behaviour, making cybersecurity more closely linked to functional safety.[47] [48]

While connected road vehicles illustrate these risks clearly, similar vulnerabilities are emerging across aviation, rail, unmanned systems, and logistics networks. In commercial aviation, modern aircraft are increasingly described as cyber-physical systems, with flight operations, maintenance, and navigation relying on interconnected software, communications links, and remote data exchange.[49] Industry and regulatory bodies such as the International Air Transport

Association (IATA) and the U.S. Federal Aviation Administration have warned that cyber intrusions affecting aircraft systems or supporting ground infrastructure can escalate into flight safety, dispatch reliability, or air-traffic-management risks, particularly as connectivity and AI-enabled decision-support tools expand.[50]

Rail systems face similar challenges. The digitalization of signaling, train control, and traffic-management systems has introduced new cyber-physical attack surfaces, especially where legacy infrastructure is integrated with modern, networked platforms. Recent analyses of European and global rail networks highlight that vulnerabilities in operational technology, such as signaling and control communications, could allow remote disruption of train movements or safety-critical systems, with implications for passenger safety and national logistics resilience.[51]

Unmanned and autonomous mobility systems, including drones, represent another high-risk category. Uncrewed aerial vehicles increasingly rely on AI-based perception and GPS-dependent navigation, making them susceptible to cyber manipulation such as signal spoofing or data-input attacks. Peer-reviewed research and real-world demonstrations have shown that adversaries can alter a drone's perceived position or environment, potentially redirecting or disabling systems used for delivery, inspection, emergency response, or defense applications. [52] These vulnerabilities directly link cyber compromise to physical behaviour in the airspace.

Cyber-physical risk also extends to logistics and freight mobility, particularly in ports and automated terminals that rely on AI-enabled scheduling, autonomous vehicles, and connected control systems. Major ports are adopting AI to optimize container handling, traffic flow, and predictive maintenance. Security agencies and industry analysts, however, have noted that disruptions or ransomware incidents targeting terminal operating systems can halt physical cargo movement, delay supply chains, and create cascading economic effects.[53] As logistics infrastructure becomes more automated, cybersecurity weaknesses increasingly equate to system-wide mobility failures rather than isolated data breaches.

Across these domains, AI-enabled systems introduce additional security concerns because adversaries can manipulate inputs, sensor data, or model behaviour rather than simply breaching networks. Small perturbations to environmental signals, navigation data, or perception inputs can cause AI systems to misinterpret conditions and act unpredictably. Unlike traditional mechanical failures, these vulnerabilities directly affect how systems perceive and respond to the physical world, tightening the link between cybersecurity and functional safety.

In defence and security applications, AI-enabled systems introduce new cyber vulnerabilities that opponents can actively exploit, rather than just accidental safety issues. As militaries adopt more autonomous and software-defined platforms, including vehicles and other cyber-physical systems, attackers can move beyond traditional network intrusion and instead target the integrity and reliability of the AI models those systems depend on. By manipulating the data and inputs that feed these models, adversaries can degrade or distort how an AI-enabled system interprets its environment, potentially disrupting movements, complicating logistics, or undermining commanders' confidence in the systems that support operations.[54]

As a result, mobility industries are increasingly treating cybersecurity as a core safety requirement alongside mechanical and functional safety. This shift is reflected in regulatory and standards development, including UNECE Regulation R155 for road vehicles, aviation cybersecurity guidance from ICAO and IATA, and rail-sector alignment with IEC 62443 and NIS2 requirements. As AI capabilities and cross-modal connectivity continue to evolve, managing cyber-physical risk remains a foundational condition for trustworthy AI across the full mobility ecosystem.

## 2. AI in Automotive and Mobility Systems

AI is increasingly embedded across the automotive and mobility sector, transforming how vehicles are designed, manufactured, and operated, as well as how mobility services are delivered and experienced. From vehicle engineering and production to fleet operations and connected infrastructure, AI is enabling more efficient, adaptive, and data-driven systems across the value chain.

This section explores how AI is applied across key areas of the automotive and mobility ecosystem, including research and development, manufacturing, supply chains, and mobility services. It highlights how these applications are improving operational performance, enabling new capabilities, and shaping the evolution toward connected, software-defined, and service-based mobility systems.

## 2.1 AI in Vehicle Research and Development, Design, & Engineering

AI is increasingly embedded across the vehicle research, design, and engineering lifecycle, reflecting a broader shift toward software-defined vehicles and data-driven development practices. AI is now used across multiple stages of development, from early concept exploration and design optimization to system validation and long-term performance management.

### AI Applications across R&D and Design

Within research and development (R&D) and design functions, AI is applied across several key use cases, including generative design, structural optimization, and simulation-based validation. In early-stage vehicle design, generative AI is being adopted as a decision-support tool to help companies explore design alternatives more efficiently. Designers and engineers can specify high-level constraints such as vehicle dimensions, weight targets, safety requirements, material choices, and sustainability goals. The model then generates multiple viable design options for evaluation. This approach supports faster iteration, helps identify trade-offs earlier in the process, and reduces reliance on physical prototyping, which can be costly and time-consuming.[55]

Beyond concept development, AI is used to support structural and materials optimization. By evaluating a large number of configurations simultaneously, AI-generated designs can identify opportunities to reduce material use while maintaining strength, durability, and safety performance. Academic research highlights that such optimization is particularly important as vehicles incorporate advanced materials, electrified powertrains, and additional onboard computing, all of which introduce new weight and thermal management considerations. These capabilities are especially relevant for electric and automated vehicles, where efficiency gains directly affect range, energy consumption, and overall system performance.[56]

AI also plays a growing role in virtual testing and system validation, complementing traditional physical testing. Research finds that simulation-based approaches supported by AI allow developers to evaluate vehicle designs and automated driving systems across a wider set of operating conditions than would be feasible through on-road testing alone.[57] Virtual environments enable repeatable testing, examination of rare or high-risk scenarios, and consistent comparison of system performance across software versions. While physical testing remains essential, these AI-enabled methods help improve coverage and reduce uncertainty earlier in the development process.

Agentic AI extends these capabilities further by orchestrating the design and validation process as a whole, rather than supporting individual tasks in isolation. Where generative AI produces design options and simulation tools evaluate them, agentic systems can coordinate across both. Agentic AI can autonomously manage workflows that span conceptual design, structural analysis, aerodynamic simulation, cost estimation, and documentation with minimal human handoff between steps. McLaren Automotive, for example, has embedded agentic AI across its engineering lifecycle using an integrated compute platform, compressing simulation and design exploration cycles from months to hours.[58]

### From Fixed Architectures to Software-Defined Platforms

Beyond specific applications, AI is also reshaping how vehicle systems are architected, deployed, and managed over time, influencing core engineering approaches, system design, and governance.

A foundational concept shaping these engineering decisions is the Operational Design Domain (ODD). The ODD is developed by the Society of Automotive Engineers' International On-Road Automated Driving (ORAD) Committee. It defines the ODD as the specific conditions under which a driving automation system or feature is designed to operate, including environmental, geographic, temporal, traffic, and roadway constraints.[59] The ODD framework is defined

under six levels of ADAS and automated driving (AD). At lower levels of automation (L0–L2), the driver remains fully responsible for monitoring the driving environment, with the system providing limited assistance for steering and/or speed control. Intermediate levels (L2+ and L3) introduce more advanced automation under defined conditions, with a transition of responsibility beginning at Level 3, where the system assumes responsibility within its ODD but may still request driver intervention. Levels 4 and 5 represent autonomous driving, where the system performs all driving tasks within specific ODDs (L4) or under all conditions without any driver involvement (L5).[60]

The ODD also defines the specific conditions under which an automated or autonomous driving system is designed to operate safely, including road type, speed range, weather, lighting, traffic conditions, and geographic scope. When a vehicle operates outside its defined ODD, the system must either request driver intervention or transition to a safe state. As automation increases, particularly at Levels 3 and above, the ODD becomes central to defining system capability, responsibility, and liability, and therefore directly influences engineering requirements, validation scope, and release governance.

Figure 2 depicts each level of ADAS/AD system and the progressive shift in "hands-on, eyes-on, and mind-on" requirements as responsibility moves from the driver to the system.

From a system-level perspective, this shift also changes how long-term performance and safety are managed. As noted previously, vehicles must be designed not only to perform reliably at launch, but to remain dependable as software is updated, features are expanded, and driving environments evolve. As a result, greater attention is placed on lifecycle management, transparency of system behavior, and the ability to demonstrate that changes introduced after deployment do not compromise safety or reliability. These considerations are especially important for higher levels of automation.

**Figure 2: Six levels of ADAS/AD systems**

| | Levels | Sample Features | Hands on | Eyes on | Mind on |
|---|---|---|---|---|---|
| Assisted | L0 Manual | Automatic emergency braking | Driver | Driver | Driver |
| | L1 Assisted driving | Adaptive cruise control (ACC); Lane Keeping assist system (LKAS) | Driver | Driver | Driver |
| | L2 Partially automated driving | Coupled ACC & LKAS | Driver | Driver | Driver |
| | L2+/++ Advanced partially automated driving | Navigate on Autopilot; Driver must be able to immediately take full control whenever requested | System | Driver | Driver |
| Automated | L3 Automated driving under conditions | Traffic jam pilot; Valet parking. Critical change: liability switches from the driver to the system | System | System | Driver |
| Autonomous | L4 Autonomous driving under conditions | Autonomous driving in approved ODDs; Can differentiate between L4 Highway and L4 Urban, due to their different complexities | System | System | System |
| | L5 Autonomous driving in all conditions | Ubiquitous autonomous driving | System | System | System |

Driver System

Source: World Economic Forum, 2025

In this context, software-defined platforms require structured deployment and oversight processes to manage change over time. Updates are introduced in stages, supported by defined approval steps, ongoing monitoring of system behaviour after release, and mechanisms to intervene if issues arise. Cybersecurity and data governance are embedded within these processes, reflecting the need to protect system integrity, ensure accountability, and meet evolving regulatory expectations across the vehicle lifecycle.

## 2.2 AI Across the Automotive & Mobility Value Chain

### Upstream Critical Minerals: Exploration, Extraction, and Processing

Electrification is changing what constrains automotive production. For electric vehicles (EVs), batteries are a primary driver of cost, vehicle performance, and long-term durability. This shifts competitive focus upstream, where access to battery-grade materials and processing capacity can determine how quickly manufacturers scale output and how reliably they meet cost and warranty targets.[61]

Rapid EV growth is therefore increasing demand for lithium, cobalt, nickel, and rare earth elements, placing greater emphasis on exploration, extraction, and processing within the battery value chain.[61] In response, mining companies and emerging technology firms are deploying AI, automation, and advanced analytics to improve how mineral resources are identified, extracted, and refined.[62]

#### AI-enabled Exploration & Discovery

Exploration remains a high-uncertainty stage, and published estimates suggest that only about 1 in 1000 prospects becomes a profitable mine.[63] AI-enabled exploration seeks to improve this conversion rate by applying ML to large, multi-source geoscience datasets, including geological maps, geochemical assays, geophysical surveys, remote sensing imagery, and drilling logs.[64] In this context, AI is used to integrate heterogeneous evidence and generate prospectivity mapping that ranks candidate areas for follow-up work and helps focus drilling on the most promising zones.

For instance, Goldcorp (acquired by Newmont in 2019) partnered with IBM to deploy IBM Exploration with Watson at its Red Lake gold operations in Ontario. The system applied ML and geospatial analytics to more than 80 years of heterogeneous exploration data, including geological maps, drill logs, and geochemical results. The AI system was used to independently validate human-generated drill targets and to propose new exploration targets. Goldcorp reported that Watson-generated targets identified gold mineralization at predicted depths, supporting follow-up drilling decisions. Importantly, this system was not a standalone experiment: it was integrated into Goldcorp's ongoing exploration workflow and subsequently recognized by the Information Technology Association of Canada.[65]

Approaches generally include supervised learning, where models are trained on known deposits to predict prospective areas and support tasks such as resource modeling, and unsupervised learning, where clustering and anomaly detection are used to surface unusual geochemical or geophysical signatures in unlabeled datasets.[66] A further step is data fusion, where magnetic, gravity, and electromagnetic survey data can be combined with satellite imagery and surface geochemistry in a unified model so signals from different disciplines corroborate one another and uncertainty can be managed more explicitly.[62] Evidence also highlights that data preparation is often a major effort, including cleaning and normalizing inputs across data types and handling noise and missing values, and that outputs still require expert geological validation to manage false positives and local context.[67]

#### AI-enabled Extraction & Processing Optimization

Once a deposit is identified, AI-enabled extraction and processing focus

on improving operating performance across two domains: (1) real-time process monitoring and optimization, and (2) equipment and asset performance management. In the first domain, AI is applied to optimize unit operations such as crushing, grinding, flotation, and thickening. Digital twin approaches support this shift by running a virtual replica of a process or piece of equipment in parallel with the real system. By combining physical models with ML and live sensor inputs, operators can simulate parameter changes and forecast impacts on recovery, throughput, and resource efficiency without disrupting production.[68]

In the second domain, AI supports equipment and asset performance management by improving how operators sense asset condition, detect anomalies, and plan interventions. ML soft sensors infer hard-to-measure variables such as ore grade, slurry density, or equipment wear from readily available sensor streams.[69] Anomaly detection and predictive maintenance models use signals such as vibration, current, temperature, and pressure to flag early signs of faults and reduce unplanned downtime.[70] CV is also widely used in processing and material handling, including ore sorting and image-based monitoring of conveyors and flotation froth, reflecting demand for faster and more consistent measurements than manual sampling alone.

## Implementation Considerations

Across exploration, extraction, and processing, AI-enabled approaches can support faster targeting cycles, higher utilization of equipment and plants, and improved recovery and output quality. They can also reduce resource intensity by lowering energy and water use per unit of output and by narrowing physical disturbance when higher-confidence targets reduce unnecessary drilling and rework.[71] However, outcomes are not uniform. Performance depends on the availability, quality, and interoperability of data, which can be uneven in greenfield exploration and inconsistent across legacy mine and plant systems that were not designed to produce standardized, analysis-ready data streams. As a result, AI performance and reliability challenges tend to surface in different ways across exploration and operations, requiring tailored controls at each stage.

- **Exploration data quality and uncertainty**: In exploration, limited ground-truth labels and sparse or noisy datasets increase the risk of false positives, meaning models may flag anomalies that do not translate into economically viable deposits. This makes uncertainty management and expert geological review essential, both to validate model outputs against local context and to decide where additional sampling or drilling is warranted.[71]
- **Operational drift and model degradation**: In operations, model performance can degrade as ore characteristics shift, equipment conditions change, or sensors drift over time, so a model that performs well during one period may become less reliable as inputs and operating regimes evolve. This increases the need for monitoring, recalibration, and clear integration into day-to-day control and maintenance workflows so predictions lead to timely actions and feedback loops that keep models current.[71]

Additional challenges relate to trust, scaling, and implementation capacity. Model interpretability matters because geologists and operators may be reluctant to act on "black box" recommendations when decisions involve major capital allocation, safety, or production risk.[71] Upfront investment and specialized skills can also be significant for autonomy, advanced sensing, and integrated process-control platforms, particularly where sites require upgrades to connectivity and data infrastructure. Scaling from pilots to mine-wide deployments often requires integration with existing operational technology, standardized data

**What does "black box" mean in AI?**

A "black box" model is an AI system that produces an output without providing a clear, human-understandable explanation of how it reached that result.

pipelines, and sustained change management, and the return on investment can be difficult to quantify consistently when commodity prices, ore variability, and operating conditions change. Emerging techniques such as direct lithium extraction and bioleaching are especially sensitive to local chemistry and operating conditions, so they require site-specific validation and staged scale-up.[72] [73] Additionally, workforce transition, permitting, and community acceptance remain relevant considerations, since expanded automation and accelerated development can affect jobs, local environmental impacts, and the social licence to operate.[74]

## Midstream: Production and Automation

### Smart Factories & Digital Twins

AI-enabled smart factories, often associated with Industry 4.0 (i.e., digitally connected, data-driven manufacturing using sensors, automation, and analytics), are becoming a core feature of modern automotive manufacturing.[75] These initiatives focus on connecting machines, sensors, and information systems across production lines and applying AI-driven analytics to monitor, analyze, and optimize operations.

Leading automotive manufacturers are advancing the "factory of the future" concept by integrating AI with other advanced technologies. Tesla has pursued a highly automated manufacturing model across its Gigafactories, a strategy described by its CEO as building "the machine that builds the machine."[76] Tesla integrates AI, Internet-of-Things (IoT), and robotics at scale, using ML to optimize robot deployment on assembly lines and analyze production data for continuous improvement. The company also applies AI-driven systems to detect and correct manufacturing defects in real-time, supporting higher quality and throughput.

Toyota has taken a complementary approach by integrating AI capabilities into its established Toyota Production System, which emphasizes just-in-time production and Jidoka, or automation with a human-centred focus. Between 2022 and 2024, Toyota's Production Digital Transformation department developed an in-house AI platform using a hybrid cloud architecture. This platform allows frontline factory workers to develop and deploy custom ML models for their specific processes through simplified web-based interfaces. As a result, more than 1,200 Toyota employees have trained AI models across 10 manufacturing plants, supporting applications ranging from visual inspection to optimizing material flows along production lines.[77] By 2024, the platform was reported to save more than 10,000 labour hours annually, contributing to measurable improvements in productivity and manufacturing quality.

Automakers are also applying digital twins at multiple levels of scale, ranging from individual robotic workcells to full production facilities. BMW provides one such example. At its Munich plant, the company implemented a comprehensive digital twin to support a major transition toward EV manufacturing. According to the company, every product and production process is planned virtually in advance.[78] This approach enables assembly line changes and new model integrations to be optimized digitally, reducing disruption during physical implementation. AI-enabled factory simulations allow BMW to test alternative workflows and scenarios and then implement changes with greater confidence.

**Digital Twins in Automotive Product Development Manufacturing**

Digital twins are virtual replicas of physical systems that bridge the gap between the physical and digital worlds. In automotive, they are used to optimize manufacturing processes and quality, and, in vehicle development, to simulate real-world operating and driving conditions for design and validation.

BMW has also applied digital twin technology to specific manufacturing processes, including welding operations.[78] Real-time data from new measurement systems is transmitted to the cloud, where

AI algorithms automatically adjust robotic welding programs during production cycles. Updated instructions are sent back to the robots without stopping the line, allowing components to be welded at optimal positions. This closed-loop system has reduced production stoppages, improved weld quality, and increased overall efficiency. More broadly, BMW has scanned all of its factories into digital models, creating current "as built" digital twins of facilities and equipment. These models are continuously updated with sensor data to ensure alignment with real-world conditions. As a result, engineers can experiment virtually with layout changes or new production methods and assess impacts on throughput, ergonomics, and resource use before committing to physical modifications.

When effectively deployed, digital twins can deliver significant operational benefits. Manufacturers have reduced time-to-market for new vehicle models by streamlining design validation and production planning in software, while also avoiding costly physical rework by identifying issues in virtual environments.[75] Beyond product development, digital twins are increasingly being applied to both greenfield facility design and brownfield modernization, where dynamic, AI-enabled simulations allow teams to test layouts, automation strategies, and material flows in advance of construction or reconfiguration. This approach supports better coordination across engineering, operations, and suppliers, reducing schedule delays and capital overruns that frequently affect large manufacturing programs.[79] Digital twins also support greater manufacturing resilience. Detailed models of production and logistics systems allow manufacturers to simulate disruptions and test contingency strategies, such as rerouting parts flows or rebalancing line workloads, in response to supply chain shocks.[80]

### AI-Enabled Drivetrain Control and System Validation

Machine learning is increasingly being used within vehicle drivetrains to improve how electric motors are controlled and tested. Research published by the IEEE shows that neural-network-based approaches can help optimize motor behavior by continuously adjusting control settings as operating conditions such as variations in temperature, load, or speed change.[81] Rather than relying only on fixed control rules, these AI-enabled systems can respond dynamically to real-world conditions, helping maintain performance and efficiency across a wider range of use cases. The same research demonstrates how these control approaches can be tested and refined using hardware-in-the-loop (HIL) environments, where real vehicle components are connected to simulated operating conditions in a controlled setting. This allows engineers to validate performance earlier and reduce risk before systems are deployed in vehicles.[81] As vehicles become more software-defined, these AI-enabled control and validation methods support faster development cycles and more adaptable drivetrain performance over the vehicle's lifetime.

### AI-Enabled Predictive Maintenance

AI-enabled predictive maintenance refers to the use of AI to monitor equipment condition and anticipate failures before they occur, allowing maintenance to be performed based on actual asset health rather than fixed schedules. According to IBM, AI-driven predictive maintenance systems continuously analyze operational data to identify early warning signals of equipment degradation, reducing reliance on reactive repairs and time-based preventive maintenance.[82] This approach helps manufacturers reduce over-maintenance, improve asset availability, and better control the timing of maintenance activities within production environments.

At a technical level, predictive maintenance relies on ML models trained on historical and real-time sensor data, such as vibration, temperature, pressure, and electrical signals.[70] Research literature shows that supervised learning models are commonly used for fault classification and remaining useful life (RUL) estimation when historical failure data is available, while anomaly detection techniques

are applied in situations with limited labeled data. More recent studies highlight the growing effectiveness of deep learning models, particularly convolutional neural networks (CNNs) and long short-term memory networks, which are well suited to capturing nonlinear degradation patterns and time-dependent behavior in industrial equipment. Comparative evaluations show that hybrid deep learning models can achieve predictive accuracies exceeding 95 percent in industrial fault detection and RUL estimation, outperforming traditional ML approaches in complex manufacturing settings.[70]

Automotive manufacturers have applied these capabilities in production settings where equipment failures can quickly disrupt tightly coupled assembly lines. General Motors (GM) has deployed ML-based predictive maintenance across multiple assembly and powertrain plants to monitor assets such as robotic arms, conveyors, paint systems, and stamping presses. Sensor-enabled AI models detect abnormal operating patterns and allow maintenance teams to address emerging issues during planned downtime, significantly reducing unexpected line stoppages and increasing efficiency.[83] Similarly, Toyota has integrated AI-based monitoring into injection molding and adhesive application processes, using sensor data to detect anomalies and performance drift before equipment damage or quality defects occur.[77] These applications link maintenance decisions directly to production stability and product quality, reinforcing the role of predictive maintenance as a core operational capability in modern automotive manufacturing.

### AI Quality Inspection

AI-enhanced quality control applies AI to automate inspection and verification tasks that have traditionally relied on manual visual checks. In automotive manufacturing, where vehicles are assembled from thousands of components at high speed, maintaining consistent quality through human inspection alone is increasingly difficult. Industry guidance from IBM notes that AI-based visual inspection enables continuous, full-line inspection at production speed, reducing variability caused by human fatigue while supporting earlier detection of defects throughout the manufacturing process.[84]

AI-enabled quality inspection is primarily driven by CV systems that combine high-resolution cameras with deep learning models. Peer-reviewed studies of industrial visual inspection show that CNNs have become the dominant approach for defect detection because they can automatically learn relevant visual features such as scratches, porosity, missing components, or misalignment directly from images. These models are more robust than traditional rules-based machine vision systems, particularly in environments with variable lighting, surface reflectivity, and part geometry.[85] Review studies report that AI-based visual inspection improves detection accuracy while enabling near-100 percent inspection coverage, supporting the transition from sampling-based quality control toward continuous inspection models aligned with zero-defect manufacturing principles.[86]

BMW provides a complementary example of AI-enabled quality control at scale. The company's AIQX (Artificial Intelligence Quality Next) platform uses camera-based CV and deep learning models to verify correct part installation, detect surface and assembly defects, and continuously monitor quality across vehicle production lines. BMW reports that AI-supported inspection enables quality checks to be performed in fractions of a second and prevents defects from propagating downstream by triggering immediate intervention when deviations are detected.[87] More recently, BMW has expanded AI-based inspection to dynamically tailor quality checks to individual vehicles based on configuration and production data, further strengthening First Time Quality and reducing reliance on manual end-of-line inspections.[88] Similar approaches are being adopted by other automakers, including Audi, which uses AI-powered vision systems to detect weld spatter and surface defects during body construction, preventing downstream damage and quality issues before vehicles progress to later assembly stages.[89]

Collectively, these applications support a shift toward zero-defect or "smart quality" manufacturing. By enabling earlier defect detection, reducing inspection variability, and tightening feedback loops between inspection and production processes, AI-driven quality control improves manufacturing stability, reduces rework and warranty exposure, and protects brand reputation. When integrated with digital traceability systems that record inspection results at each production stage, AI-enabled inspection strengthens end-to-end quality governance across automotive manufacturing and supplier networks.

### Robotics & Production Optimization

The automotive industry has historically been a leading adopter of industrial robotics, particularly in applications such as welding, painting, assembly, and material handling.[90] Recent advances in AI are expanding the capabilities of these systems, enabling more adaptive and intelligent forms of automation within automotive manufacturing environments. According to the International Federation of Robotics, automotive manufacturing remains one of the most highly automated industrial sectors. In 2024, approximately 40 percent of all new industrial robots installed in the United States were deployed in automotive plants. [90] Globally, South Korea leads overall robot density for manufacturing, with 1,220 robots installed per 10,000 manufacturing employees, followed by Singapore (818), Germany (449), and Japan (449). [91] While traditional industrial robots have typically been pre-programmed to perform repetitive tasks, AI is increasingly redefining what these systems can do.

As described earlier, the integration of ML, CV, and advanced sensor technologies is enabling a new generation of robots capable of perceiving and responding to their physical operating environment. Industry experts often describe this convergence as physical AI, referring to robotic systems that can sense conditions, learn from data, and make limited real-time decisions.[92] In practical terms, this allows robots to manage greater variability and perform more complex or precision-oriented tasks. For example, AI enables adaptive assembly processes, in which robots adjust their movements based on continuous feedback from cameras and sensors.

A related development is the growing adoption of collaborative robots, or cobots, which are designed to work safely alongside human operators. [93] Unlike traditional industrial robots that operate within restricted safety enclosures, cobots use sensors and AI algorithms to detect human presence and dynamically adjust force and speed, allowing direct collaboration on tasks such as assembly support, material handling, or component retrieval. As noted by Massachusetts Institute of Technology robotics researchers, future robots are expected to move beyond repetitive tasks to collaborate with humans, adapt to changing workflows, and learn new skills without extensive reprogramming. Automotive manufacturers are actively exploring these approaches. GM, for example, has established a dedicated Robotics Strategy division focused on integrating more flexible, human-centred robotic systems within its plants.[94] GM's approach emphasizes the use of robots to perform physically demanding, hazardous, or repetitive tasks, while human workers concentrate on problem-solving, oversight, and process improvement. This philosophy reflects a broader industry consensus that intelligent robotics should augment, rather than replace, human labour. Practical applications include robots lifting heavy components, performing overhead welding to reduce ergonomic strain, and transporting parts across factory floors using autonomous guided vehicles coordinated by AI-based scheduling systems.

Automakers such as Tesla have pushed the boundaries of robotics adoption, with assembly plants that rely extensively on robotic systems for tasks such as welding and painting. Tesla is also developing a general-purpose humanoid robot, known as "Optimus", with the long-term objective of automating additional factory and logistics activities.[95] While humanoid robots remain largely experimental, the broader trend across the industry is the enhancement of existing industrial robots through AI retrofitting and the development of new

robotic systems designed with AI capabilities from the outset.[96] Rather than replacing legacy equipment entirely, manufacturers can deploy AI-enabled vision, control, and edge-computing systems that integrate with existing robots, enabling functions such as contextual awareness, real-time decision-making, and adaptive responses to changing conditions, including pausing operations when humans enter close proximity or adjusting movements to accommodate different part orientations.[97]

The operational benefits of AI-enabled robotics are substantial. They contribute to improved workplace safety by assuming responsibility for the most hazardous tasks, such as paint spraying or handling heavy components.[98] In addition, AI-guided robots provide greater production flexibility, as they can be reconfigured or reassigned to different models or processes more rapidly than traditional automation, supporting faster production line changes with minimal downtime. These capabilities are increasingly important as automakers respond to fluctuating demand, model diversification, and heightened competitive pressures.

While robotics and physical AI systems continue to advance in capability and autonomy, they are still not able to operate independently of human involvement.[99] High implementation costs, technical integration challenges, and gaps in workforce skills remain significant constraints. These limitations have shifted the conversation away from full automation toward more balanced operating models. Rather than replacing human labour, intelligent machines are increasingly positioned as collaborative tools that extend human capacity. The emerging consensus emphasizes joint human–AI systems, where automated technologies handle structured, repetitive, or precision-driven tasks, while people retain responsibility for supervision, complex judgments, creative problem-solving, and process adaptation.

The following table summarizes the specific company examples discussed in this section, highlighting how AI is applied in manufacturing and the outcomes reported by each company.

**Table 2: Examples of Automaker Companies Leveraging AI in Manufacturing**

| Company | AI Applications in Manufacturing | Outcomes / Benefits |
|---|---|---|
| **Tesla** | Highly automated smart manufacturing across Gigafactories; extensive use of robotics supported by AI; ML-driven production analytics for continuous process optimization; AI-enabled defect detection and real-time quality monitoring. | Enables high-volume EV production with improved efficiency, faster assembly, and tighter process control. AI supports higher throughput, reduced error rates, and consistent build quality across production lines. |
| **Toyota** | In-house, company-wide AI platform enabling frontline factory workers to build and deploy ML models for visual inspection, process optimization, and material flow improvement; integration with existing Toyota Production System practices. | More than 10,000 labour hours saved annually through productivity and quality improvements. Supports workforce-led AI adoption and scalable smart-factory deployment across multiple plants. |
| **BMW** | Factory-scale and process-level digital twins for production planning and EV transition; AI-enabled simulations to test workflows and line changes; AI-driven closed-loop control for robotic welding; AI-based in-line quality inspection. | Faster ramp-up of new models and reduced disruption during EV manufacturing transitions. Virtual validation improves implementation speed, while real-time AI corrections reduce line stoppages and improve first-time quality. |

| Company | AI Applications in Manufacturing | Outcomes / Benefits |
|---|---|---|
| **General Motors (GM)** | ML-based predictive maintenance using sensor data across assembly and powertrain plants; AI models to detect abnormal equipment behavior; AI-enabled monitoring integrated into scheduled maintenance workflows. | Reduced unplanned downtime and fewer unexpected line stoppages. Improved production stability by addressing equipment issues before failures disrupt tightly coupled assembly lines. |
| **Audi** | AI-powered computer vision systems for defect detection during body construction, including weld spatter and surface defect identification. | Earlier defect detection prevents damage from propagating downstream, improving body quality and reducing rework later in the assembly process. |

## Downstream: Battery Lifecycle Management and Automotive Services

### AI for EV Battery Lifecycle Management

Accurate assessment of battery health is critical for EV reliability, resale value, and lifecycle optimization. AI has significantly improved prediction capabilities in these areas.

#### 1) Battery Health Monitoring and Predictive Maintenance

An EV's battery is both its most expensive component and a critical determinant of performance, safety, and long-term ownership costs. As a result, managing battery health has become a top priority for automakers.

Historically, assessing an EV battery's State of Health (SoH), including how much capacity it has lost over time and how it is likely to perform as it ages, required extensive laboratory testing. Battery cells would be cycled hundreds of times under controlled conditions to observe degradation patterns, a process that could take months or years.[100] ML models now allow long-term battery degradation to be predicted after observing only a limited number of early charge-discharge cycles. Research has shown that certain early-life indicators, such as voltage behaviour, temperature response, and charging patterns, can be strong predictors of future capacity loss.[100] This capability accelerates research and development of longer-lasting battery chemistries and enables earlier detection of manufacturing defects by identifying cells whose early performance deviates from expected "healthy" profiles.

Once a battery pack is deployed in a vehicle, its battery management system (BMS) continuously monitors parameters such as cell voltages, current flow, temperature, and charging rates.[101] AI-enhanced BMS solutions can deliver more precise estimates of state of charge and SoH, reducing uncertainty in range predictions and supporting optimized performance without accelerating battery degradation. For example, an AI-based system may support optimized fast-charging strategies within established safety and thermal constraints, potentially reducing charging time for the driver without materially affecting battery life.[101] Conversely, if a particular cell consistently underperforms, the system can detect the imbalance and apply appropriate management strategies, such as cell balancing, to reduce stress and extend its usable life.[102]

AI can also support improved charging strategies that balance convenience, cost, and battery longevity. Predictive charging systems can take into account user driving patterns, electricity pricing, grid conditions, and battery wear characteristics to recommend optimal charging times and charge levels.[103] For example, if a vehicle is typically used for a morning commute, the system may delay charging until early morning hours when electricity prices are lower and the battery is cooler, and limit charging to 80 percent if a full charge is not required for the day's travel. While users retain the ability to override these recommendations, many opt into AI-guided charging for its convenience and long-term benefits. Fleet operators use similar AI-based approaches to manage charging across large numbers of

vehicles, staggering charging sessions to avoid demand charges, prioritizing vehicles scheduled for imminent use, and coordinating with depot energy management systems to minimize costs.[104] In this context, AI treats the battery not as a static component, but as a dynamic asset that can be actively managed and optimized throughout its lifecycle.

Collectively, these AI-enabled approaches have direct implications for costs, safety, and customer experience. EV batteries are typically warranted for eight to ten years or a defined mileage threshold, and even modest improvements in lifespan or reliability can translate into significant reductions in warranty replacement costs while strengthening perceptions of durability.[105] Early detection of battery faults also contributes to safety by reducing the risk of rare but serious incidents such as thermal runaway. As EV adoption continues to scale, AI-driven battery health monitoring and predictive maintenance are rapidly becoming standard practices across the automotive industry.[106]

### 2) Second-Life Applications and Battery Recycling

EV batteries are not discarded once they can no longer meet the performance requirements of automotive use. When a battery's capacity declines to approximately 70 to 80 percent of its original level, typically after eight to twelve years of service depending on vehicle usage, it may no longer provide sufficient driving range but can still deliver significant value in less demanding applications.[101] Deploying batteries in second-life uses, such as stationary energy storage, followed by eventual recycling to recover raw materials, is a critical strategy for reducing waste and lowering the total cost of EV ownership. AI plays an important role both in determining the most appropriate end-of-life pathway for batteries and in optimizing the execution of second-life deployment and recycling processes.

When an EV is retired or its battery is replaced, the first step is determining whether the battery is suitable for reuse. Used batteries vary significantly in condition. Some retain substantial capacity but lack the power needed for high-performance driving, while others may contain degraded cells, imbalances, or physical damage that limit their suitability for second-life applications. Historically, assessing these conditions required time-intensive testing. Increasingly, automakers and specialized startups are using AI to automate this evaluation process. By analyzing historical data extracted from a battery's BMS and comparing it against known degradation patterns, ML models can rapidly classify batteries across multiple health and safety criteria. This results in a data-driven "health certificate" indicating whether a battery is suitable for reuse and, if so, what type of second-life application is appropriate. For example, a battery that experienced frequent fast charging and exhibits cell voltage variability may be directed toward immediate recycling, while one with moderate, consistent usage in stable climates may be identified as a strong candidate for repurposing.[107] This AI-enabled triage process ensures that reusable batteries are not prematurely recycled and that only safe, high-performing batteries are redeployed.

Once deemed suitable, used EV batteries can be aggregated into stationary energy storage systems for residential, commercial, or grid-level applications. Managing collections of second-life batteries presents operational complexity, as individual units may differ in capacity, age, and performance characteristics.[108] Energy providers are using AI-based control systems to manage these heterogeneous assets efficiently. AI algorithms can dynamically balance charge and discharge loads across battery modules to optimize system performance and extend overall lifespan. A prominent real-world example is Redwood Materials, which has launched its "Redwood Energy" initiative to build energy storage systems from retired EV battery packs.[109] In 2025, Redwood unveiled a 12 MW/63 MWh microgrid powered entirely by repurposed EV batteries, representing the largest second-life battery storage installation in North America. Developed in partnership with Crusoe Energy, the system uses AI-driven controls to manage charging and discharging at the module level, delivering reliable power to energy-intensive applications, including an off-grid

data centre supporting AI computing. By applying AI to coordinate this diverse set of used batteries, Redwood maximizes efficiency, reliability, and safety while creating new revenue streams from assets previously considered waste. This approach effectively extends battery value by delaying recycling and extracting additional economic and environmental benefit.

When batteries reach true end of life, recycling becomes essential to recover lithium, cobalt, nickel, and other critical materials.[61] Battery recycling is a complex, multi-stage process involving disassembly, shredding, material separation, and chemical extraction. Improving recovery efficiency is a priority, as even small increases in yield can significantly reduce the need for new mineral extraction.

Machine vision and robotics are being used to automate battery identification and disassembly. Given the wide variation in battery pack designs across manufacturers, AI-enabled robots can be trained to recognize different configurations and dismantle them more safely and efficiently than manual processes.[110] In addition, AI supports capacity planning and supply forecasting. By analyzing EV adoption trends and battery lifespan data, AI can help recyclers anticipate future volumes of end-of-life batteries and scale recycling infrastructure accordingly. The International Energy Agency projects that used EV batteries equivalent to approximately 560 GWh per year will become available for recycling by 2040, a volume that will require advanced automation and intelligence to process efficiently.[61]

Through the combined application of second-life utilization and optimized recycling, the automotive industry can substantially reduce the environmental footprint of EVs. AI enables value maximization at each stage of the battery lifecycle: extending usable life in vehicles, redeploying batteries in less demanding applications, and ultimately recovering critical materials for reuse in new battery production. This closed-loop approach reduces dependence on virgin mineral extraction and supports the long-term sustainability of EV battery supply chains.

## AI in Mobility Services and User-Facing Applications

As the automotive industry continues to evolve from a product-focused model toward service-based offerings, MaaS has emerged as a central enabler of platforms and connected automotive services.[111] Companies such as Uber, Lyft, Didi, automaker-led mobility brands, and public transit operators increasingly rely on AI-driven systems to coordinate vehicles, trips, and transactions in real-time.[112] These platforms have the requirement to balance supply and demand, optimize routing, maintain fleet performance, and tailor services to individual users, all at significant scale. The sections below outline the core AI-enabled applications supporting MaaS and connected mobility services, and the value they deliver across the mobility ecosystem:

### 1) Optimizing Fleet Operations with AI

For mobility operators, AI provides advanced operational intelligence that optimizes vehicle deployment and operational decisions across fleets in real-time. AI systems use live operational data to assign the most appropriate vehicle or driver to each trip request and to calculate optimal routing. For example, Uber's dispatch system does not simply match the nearest available driver to a rider. Instead, it may briefly delay assignment to batch multiple requests and solve a broader matching problem that optimizes outcomes across an entire service area.[113] This approach reduces overall wait times and increases vehicle utilization compared to simple first-come matching.[114] Similar AI-driven routing and dispatch systems are used by delivery fleets and on-demand shuttle services to reduce total miles traveled and fuel consumption while improving service reliability.[115]

Furthermore, ML models analyze historical and contextual data, including time of day, location patterns, weather conditions, and local events, to forecast rider demand.[116] Ride-hailing and car-sharing platforms use these forecasts to proactively position vehicles ahead of anticipated demand spikes, such as rush hours or large events.[114] AI systems, for example, may predict a surge in ride requests following a

concert and reroute vehicles to the area in advance. This approach reduces "deadheading miles" and improves response times for users.[117] AI-driven fleet rebalancing is also widely used in shared micromobility systems, such as bike and scooter programs, where vehicles are redistributed based on expected future demand rather than past usage patterns.[118]

Maintaining vehicle availability and minimizing downtime is another critical operational area where AI is being applied. Connected vehicles, including cars, buses, and trucks, continuously generate data on engine performance, battery health, tire pressure, braking behaviour, and other operating conditions. AI-enabled maintenance platforms, offered by providers such as Preteckt and Stratio for bus and truck fleets, analyze this data to detect early indicators of component degradation or failure.[119] [120] For instance, subtle increases in engine vibration or abnormal drops in battery voltage under load can signal emerging issues. By identifying these patterns, AI systems can alert maintenance teams weeks before a failure occurs. In MaaS environments, predictive maintenance insights are often integrated directly into dispatch and scheduling: vehicles can be proactively routed out of service during low-demand windows and replacement units can be rebalanced to maintain coverage and on-time performance. This reduces missed trips and helps platforms meet reliability targets while keeping utilization high.

Fleet operators are also deploying AI to enhance safety and regulatory compliance. AI-enabled camera and telematics systems installed in taxis, buses, and trucks can detect driver fatigue, distraction, or aggressive driving behaviours and issue real-time alerts. These systems support accident prevention while also generating data that can be used for driver training and performance improvement.[121] Some operators link AI-based safety insights to incentive programs that reward safe driving, contributing to measurable reductions in collision rates within commercial fleets.[122] In trucking and logistics operations, where regulations govern driver working hours, AI systems can optimize routing to include appropriate rest stops and flag potential hours-of-service violations before they occur, reducing compliance risk alongside service disruption risk.

### 2) Smart Pricing and Integrated Payments

AI-enabled pricing and payment systems are supporting more sophisticated, flexible, and user-centred mobility services. On the pricing side, AI algorithms dynamically adjust fares and driver compensation to balance supply and demand and maintain service quality. On the payments side, the integration of multiple transportation modes into a single platform, supported by unified payment accounts, generates rich data that AI can analyze to improve service design and enable new financial and business models.

Many mobility services rely on dynamic pricing models in which trip prices fluctuate based on real-time conditions. Uber's surge pricing is a well-known example. When demand exceeds available supply in a given area, prices increase to encourage more drivers to enter that zone and to allocate rides among users based on willingness to pay. Behind this mechanism, AI-driven pricing systems use predictive models to estimate rider price sensitivity and driver response, allowing platforms to determine the optimal pricing adjustment needed to restore balance.[123] Rather than applying a simple supply-and-demand curve, these systems learn from historical patterns and current inputs to calibrate pricing by location, time, and user segment. Comparable AI-based pricing engines are used by other platforms, including Lyft and Didi. A well-designed dynamic pricing model improves vehicle availability during peak periods, reduces the frequency of severe shortages, and increases overall fleet utilization by directing drivers to areas where demand is highest.[124]

A defining feature of MaaS is the ability for users to pay for multiple transportation modes through a single application and account. Initiatives such as Whim in Helsinki and Jelbi in Berlin illustrate how public agencies and private operators are working toward a "single

wallet" model that integrates transit, ride-hailing, micromobility, and short-term vehicle rentals.[125] When trips across different modes are linked through a unified account, platforms gain a comprehensive view of user travel behaviour. AI can analyze this data to identify common trip chains, such as combinations of transit and ride-hailing or driving and micromobility, as well as typical parking and transfer locations. These insights support service planning by both mobility operators and urban planners and enable the development of new fare products. For example, AI analysis may reveal that a segment of users consistently uses scooters for short trips to a specific train station during weekday mornings. Based on this pattern, a MaaS operator could introduce a discounted "last-mile bundle" that allows unlimited scooter trips to and from transit hubs for a flat monthly fee. AI-based simulation tools can also estimate how such pricing changes would affect ridership, including elasticity and mode-shift impacts.[126]

As mobility platforms increasingly rely on digital payments, managing fraud and misuse has become a critical concern. AI plays a key role in safeguarding payment systems by monitoring transactions in real-time and flagging anomalous behaviour, such as unusually large purchases or atypical travel patterns that may indicate account compromise or fare evasion.[127] Given the high volume of small transactions processed by mobility systems, manual monitoring is impractical. AI techniques commonly used in banking and e-commerce, including clustering and outlier detection, are therefore applied in MaaS environments to identify suspicious activity, duplicated accounts, or systematic abuse.[127] These systems enable platforms to block or challenge potentially fraudulent transactions automatically while minimizing friction for legitimate users.

AI is also enabling new asset-based business models that blur traditional distinctions between vehicle ownership, leasing, and on-demand use. Under "vehicle-as-a-service" arrangements, operators retain ownership of vehicles and provide access to drivers or fleets in exchange for usage-based payments.[128] AI is central to managing these models by assessing vehicle usage, wear, accident risk, and revenue generation through telematics data and predictive analytics. Practical examples include Renault's Mobilize unit, which provides EVs to car-sharing operators through subscription and leasing arrangements that bundle insurance, maintenance, and telematics services.[129] Vehicle usage data is transmitted back to Mobilize's platform, where AI supports maintenance scheduling and monitors utilization efficiency.[130] Automakers increasingly view these approaches as growth opportunities. Toyota's mobility subsidiary, KINTO, is expanding its portfolio of vehicle subscriptions and short-term rentals, which depends on digital fleet management and predictive analytics to preserve vehicle residual values.[131] Toyota has indicated that by 2040, mobility services are expected to represent a significant share of its overall business, a strategy that is fundamentally dependent on data-driven and AI-enabled operations.

### 3) In-Vehicle Experiences and Infotainment AI

The influence of AI extends beyond fleet-level and system-level optimization to the in-vehicle experience, where it is increasingly used to personalize interactions for drivers and passengers. As vehicles become software-defined platforms, automakers and technology providers are embedding AI-enabled features to enhance comfort, convenience, and safety. These applications represent an important downstream dimension of AI adoption, shaping how consumers interact with and experience vehicles on a daily basis.

Many new vehicles now include voice-controlled assistants that allow drivers to interact with vehicle systems using natural language. These assistants may be proprietary, for example Mercedes-Benz MBUX "Hey Mercedes" voice assistant, which integrated ChatGPT via Microsoft's Azure OpenAI Service in a 2023 pilot,[132] or part of broader technology ecosystems, such as Android Automotive with Google Assistant used by Volvo, GM, and others.[133] These systems rely on AI-based natural language understanding to support conversational

interactions similar to those offered by smartphone assistants. While smartphone assistants such as Siri or Google Assistant already enable basic hands-free tasks, next-generation in-vehicle AI assistants differ in their ability to understand context, coordinate multiple actions, and interact directly with vehicle systems. Smartphone assistants typically respond to single commands in isolation, requiring drivers to issue tasks step-by-step and often repeat information. By contrast, AI-enabled vehicle assistants powered by large language models can interpret compound requests, retain context across interactions, and execute multi-step workflows that span messaging, navigation, and communication functions in one continuous exchange. By allowing drivers to delegate tasks to AI systems, these interfaces reduce cognitive load and support safer driving by enabling hands-free interaction. As a result, voice-based AI assistants are emerging as both a convenience feature and a competitive differentiator among vehicle brands.

AI systems within vehicles also increasingly learn and adapt to individual user preferences over time. This includes automatic adjustment of seat positions, mirror angles, climate settings, and preferred audio sources for specific drivers, as well as adaptive vehicle dynamics such as suspension tuning or throttle response based on driving style. [134] Infotainment systems also use recommendation algorithms to suggest music, podcasts, or other media, similar to personalized content delivery on mobile devices.[135] Beyond comfort and entertainment, AI-enabled personalization extends to trip planning and energy management. For example, Tesla's navigation system uses AI to plan long-distance trips by routing vehicles through optimal Supercharger locations and recommending charging durations that minimize overall travel time, based on real-time charger availability and vehicle battery data.[136] This effectively functions as an AI-driven travel concierge. Other manufacturers, including Ford and Hyundai, offer similar features in their EVs, with systems that learn driver preferences for charging locations over time. Looking ahead, automakers are investing heavily in these ADAS capabilities (figure 2), as they support higher customer satisfaction and create opportunities for new revenue streams, including subscription-based premium digital features.

Downstream AI applications also include a growing range of digital services enabled by vehicle connectivity. Usage-based insurance (UBI) is one example, offered by insurers and automakers using telematics data to assess driving behavior and adjust premiums accordingly.[137] AI models analyze factors such as acceleration patterns, speed, braking behavior, and time of day to estimate risk profiles, potentially rewarding safer driving with lower insurance costs. This creates a feedback loop that encourages improved driving behavior. In-vehicle commerce and digital marketplaces are another emerging area. Platforms such as GM's OnStar allow drivers to place orders, locate services, or access promotions through the vehicle interface. More broadly, startups and automakers are exploring the vehicle as an additional channel for personalized recommendations, such as suggesting nearby services based on user preferences, location, and route context. AI systems underpin these services by ensuring that recommendations are relevant and continuously refined based on user feedback and behavior.[138]

Overall, AI is transforming vehicles into intelligent, connected platforms capable of interacting naturally with users and improving over time. This downstream application of AI affects how consumers experience and evaluate vehicles, influencing daily usage rather than just manufacturing or operational performance. Automakers including Mercedes-Benz, BMW, Tesla, Toyota, and others have established dedicated AI and software teams or partnerships to accelerate development in this area, reflecting recognition that digital intelligence is becoming as important to customers as traditional performance attributes. These AI-enabled features also allow manufacturers to remain connected to customers long after the initial sale, supporting over-the-air updates, ongoing service enhancements, and new revenue models, such as subscriptions for software-based features. This shift toward treating vehicles as platforms for continuous digital services represents a broader industry transition that depends fundamentally on

AI-driven personalization, automation, and data analytics.

## 2.3 The Connected Ecosystem: Smart Infrastructure & Mobility Operations

### AI-Enabled Smart Mobility Networks

#### Smart EV Charging

The International Energy Agency projected that the global EV fleet will grow from 20 million in 2025 to 808 million by 2040.[139] [140] This rapid growth of EVs is placing strain on power grids that were not designed for widespread EV charging. In some European jurisdictions, connecting new highway fast-charging stations can require grid upgrades that take six to twenty-four months to complete.[141]

AI can mitigate these pressures by optimizing EV charging through predictive load management and smart charging algorithms. By analyzing real-time grid conditions, charging station utilization, and weather and pricing signals, AI systems can stagger or modulate charging to avoid peak-demand spikes, support renewable energy integration, and reduce stress on local distribution networks.[141] [142] Research indicates that well-implemented smart charging strategies can reduce peak grid loads by 20 percent,[142] improving system stability and deferring costly infrastructure upgrades. AI-driven platforms can also learn from EV charging patterns to forecast demand and balance loads across EV batteries, on-site storage, and the grid, maximizing the use of cheaper or cleaner energy when available.

As these capabilities evolve, electric vehicles are increasingly being positioned not just as sources of electricity demand, but as distributed energy resources (DER) that can actively support grid operations.[143] AI-enabled platforms can aggregate and coordinate charging loads across fleets and regions, treating EVs, on-site storage, and charging infrastructure as flexible assets within the broader energy system. This shifts the role of EV infrastructure from a potential grid constraint to a foundational component of system flexibility, with the ability to absorb excess supply, respond to system peaks, and contribute to more balanced load profiles.

Advancements in vehicle-to-grid integration further reinforce this shift. AI-driven systems can enable bidirectional power flows, allowing electricity stored in EV batteries to be discharged back to the grid during peak demand periods and recharged during off-peak times. [144] Companies such as BluWave-ai in Canada and Fermata Energy in the United States have developed AI software that forecasts electricity demand and manages vehicle-to-grid interactions, allowing EVs and charging infrastructure to operate as distributed energy resources.[141] These V2G systems can automatically adjust charging rates or enable bidirectional power flows, including drawing electricity from idle EVs during peak periods and recharging vehicles when demand is lower.

Together, these developments highlight how AI-enabled smart charging is shifting EV infrastructure from a grid constraint into a flexible asset, reshaping how electricity systems plan for and manage the next phase of transport electrification.

#### AI-Enabled Traffic Optimization

Traffic congestion imposes substantial economic and social costs through lost time, fuel consumption, increased emissions, and reduced travel reliability. Traditional traffic signals often operate on fixed timing plans and cannot respond dynamically to short-term changes in demand.[145] AI and advanced sensors are enabling “smart intersections” that adapt signal timing to observed traffic flows. In Pittsburgh, for example, an AI-based traffic signal system called Surtrac has been deployed across dozens of intersections. Each signal uses cameras and radar to detect approaching vehicles and applies ML to optimize signal timing in real-time based on current traffic conditions.[145] By communicating with neighboring signals, the system coordinates movements through corridors and creates smoother “green waves.” Reported pilot results indicate the Surtrac system cut average travel times by ~25 percent, reduced time spent waiting at intersections by

over 40 percent, and lowered vehicle emissions by 21 percent through reduced idling.[145]

From a public-sector perspective, AI-based congestion management offers a way to defer or reduce the need for new road infrastructure by extracting greater efficiency from existing assets. Rather than expanding capacity through additional lanes, which is costly, land-intensive, and often politically challenging, jurisdictions can use smart signal control or AI-enhanced ramp metering to increase throughput on current roadways.[146] Several United States jurisdictions are also exploring AI-informed dynamic traffic regulations, including variable speed limits and congestion pricing, as tools to actively manage demand.

Dynamic tolling systems, already deployed on express lanes in cities such as Los Angeles, Seattle, and Singapore, adjust prices in real-time based on congestion levels to keep traffic flowing. These systems rely on predictive models and continuously updated traffic data, often enhanced by AI, to raise tolls as congestion increases and lower them when demand is light. By influencing driver behavior, these mechanisms help smooth peak travel periods and make better use of available road capacity. Evidence from Sweden illustrates the potential impact. After Stockholm introduced an AI-assisted dynamic congestion charge, traffic volumes entering the city centre declined, while annual net revenues available for public transit investment increased from approximately USD $50 million to $155 million under the new pricing model. [146] By reducing stop-and-go traffic and encouraging off-peak travel or alternative modes, these measures can reduce fuel waste and emissions while improving the efficiency of urban mobility systems.

### Connected Infrastructure & V2X

Beyond intelligent traffic lights, V2X communication is enabling direct coordination between vehicles and infrastructure. V2X encompasses vehicles communicating with traffic signals (V2I, vehicle-to-infrastructure), with other vehicles (V2V), and with pedestrians' smartphones (V2P), typically over fast wireless links. AI contributes by interpreting high-volume, real-time data streams and coordinating system responses. In a connected corridor, an AI system might receive a warning from a vehicle about sudden hard braking or a slippery road and then adjust digital speed limit signs, reroute nearby traffic, or alert approaching cars and transit vehicles. These technologies have demonstrated safety and mobility benefits.

Governments worldwide are investing in connected infrastructure as part of broader road safety and mobility modernization initiatives. In the United States, the Department of Transportation's research reports that V2X deployments have improved safety outcomes in multiple states: work zone warnings in Indiana cut hard-braking events by 80 percent, and a pedestrian-crossing alert system in Cleveland reduced bus drivers' reaction times to pedestrians by 19 percent. [147] In Tampa, Florida's connected vehicle pilot, V2V safety applications (such as forward-collision warnings) and V2I alerts (such as warnings about sudden slowdowns ahead) reduced the rate of high-risk driving scenarios by nearly 9 percent and cut average travel times by 30 percent in the pilot zone.[147] Another pilot in Alpharetta, Georgia found that a V2I-enabled "smart intersection" that provided priority to approaching school buses reduced the number of stops those buses made by 40 percent and lowered their travel time by 13 percent, while also improving fuel efficiency by 7–12 percent.[147]

These findings illustrate how AI-coordinated connected infrastructure can improve mobility and safety: when vehicles and traffic systems share data, signals can prioritize public transport or emergency vehicles, and drivers can receive real-time warnings of hazards or pedestrians ahead, reducing collision risk.

## AI-enabled Fleet Operations & MaaS

### Intelligent Fleet Routing and Dispatch

Managing a large fleet, whether buses, delivery vans, or ride-share cars, is a complex optimization problem. AI and advanced algorithms are

increasingly used to address this complexity in real-time. A widely cited example is UPS's ORION (On-Road Integrated Optimization and Navigation) system, which combines operations research techniques with ML to optimize delivery routes for the company's 55,000-vehicle fleet.[115] ORION evaluates millions of route permutations, traffic data, and package delivery windows each day to identify efficient stop sequences while respecting constraints such as promised delivery times. By continually adjusting routes to avoid congestion and reduce left turns (which can introduce delays), ORION has enabled UPS to reduce driving distance by 100 million miles annually, saving an estimated 10 million gallons of fuel each year and reducing CO2 emissions by ~100,000 tons.[148] These outcomes translate into $300–$400 million in yearly savings on fuel and operational costs, improving both cost efficiency and environmental performance. Public agencies are also increasingly examining how comparable analytics could support dispatching for on-demand shuttles and paratransit, and how pricing or incentives can shape first/last-mile connections to transit hubs.

### Demand Forecasting

At the connected ecosystem level, demand forecasting supports system-wide planning and coordination rather than individual operator optimization. Public agencies and infrastructure operators use AI-enabled forecasts to anticipate when and where mobility demand will emerge across road networks, transit systems, and shared services, enabling proactive rather than reactive management of congestion and service reliability.

Unlike platform-level forecasting used by ride-hailing or fleet operators, ecosystem-scale demand forecasting integrates signals across multiple domains, including transit ridership, road traffic volumes, special events, weather conditions, and land-use patterns.[149] These forecasts inform decisions such as adjusting transit headways, deploying additional vehicles on high-demand corridors, reallocating curb space for pickups and deliveries, or activating traffic management measures during anticipated surges. When integrated with traffic signal control, curb management, and traveler information systems, forecasting becomes a coordination tool that aligns infrastructure behavior with expected demand.

For public-sector stakeholders, forecasts can help agencies identify underserved areas, plan service adjustments for major events or disruptions, and evaluate how pricing, incentives, or temporary interventions may shift travel behavior. By embedding demand forecasting into day-to-day operations and planning processes, cities can improve network performance without relying solely on costly physical expansion, strengthening the resilience and adaptability of urban mobility systems.

## AI-Enabled Mobility Service Layers

### Open Payments (Account-Based Fare Collection)

Cities worldwide are upgrading transit fare collection to accept standard contactless bank payments and mobile wallets. This shift improves customer convenience while also generating rich transactional data that can support planning and fare policy analysis.

Dynamic pricing is used to influence travel behaviour and manage congestion. Singapore's MRT system, for example, used a data-driven approach to offer free or discounted rail trips for passengers who travelled before the morning rush hour, successfully flattening the peak by shifting some commuters to earlier trains.[150] In road transport, digital tolling systems, often underpinned by AI for traffic prediction, adjust charges in real-time on highways or central zones (congestion pricing) to maintain traffic flow. As digital payment platforms mature, it becomes increasingly feasible to integrate pricing mechanisms across modes. A commuter's single mobility account could apply a higher rush-hour road toll or, alternatively, offer a discounted transit fare to encourage mode shift on high-demand days. For public officials, AI-aided pricing tools provide a policy lever to reduce congestion and emissions while shifting demand toward underused capacity.

Mobility "Wallets" and Unified Traveller Accounts that consolidate eligibility, subsidies, and payments across multiple providers within a single account administered through a card or mobile application are being piloted by some jurisdictions. For example, Los Angeles is testing a Mobility Wallet pilot in South LA that provides low-income residents with a monthly travel stipend usable for Metro transit, bike-shares, e-scooters, and Lyft/Uber rides, all through a single card or app interface.[151] An underlying AI-enabled system can track how funds are used across modes and support analysis of travel patterns. Early results indicate that participants use the wallet across a diverse set of modes, suggesting that integrated payment access can help address first/last-mile gaps by lowering friction to try additional options.[152]

In the private sector, platform convergence can also support public transit access by distributing ticketing through widely used mobility applications. Uber has integrated public transit ticketing in some cities (e.g. Las Vegas, Denver), allowing users to view transit options and purchase a bus or rail ticket using the same account used for ride-hail services.[153] From a public-agency perspective, the relevance is the potential to reduce friction for multimodal trips while maintaining secure payment interoperability and appropriate data-sharing arrangements.

### Journey Planning & Accessibility

Within user-facing mobility services, AI is increasingly applied to journey planning, service updates, and accessibility supports that sit at the interface between travellers and the broader transportation system. As mobility becomes more digital and on-demand, personalization is increasingly used in public and shared-mobility applications to improve usability and system transparency. AI techniques, including ML and natural language processing, support customized guidance (e.g., route recommendations, disruption alerts, and service updates) and can reduce barriers for diverse user groups. For public-sector stakeholders, the primary value is improved customer experience, accessibility, and safer decision-making through clearer, more timely information.

- **Tailored journey planning and assistance:** Modern journey planning apps (e.g., Citymapper, Google Maps, or transit agency apps) already use AI to provide real-time route recommendations based on schedules and traffic conditions. An emerging direction is more proactive and personalized assistance, in which applications identify disruptions and recommend alternatives aligned with user preferences (e.g., minimizing walking or avoiding crowded vehicles) while preserving arrival-time constraints.[154] These capabilities are still developing, but elements are visible in several cities. Helsinki's Whim app, for instance, learns from a user's travel history to recommend multi-modal options tailored to observed patterns and enables saving "favourite" places and modes for quicker planning.[155]
- **Accessibility and inclusivity:** AI-driven personalization can improve accessibility by providing multi-language, multimodal interfaces and step-by-step guidance tailored to user needs. Transit agencies are deploying virtual travel assistants that operate in multiple languages and support riders with diverse accessibility requirements.[156] For instance, the Chicago Transit Authority's "Chat with CTA" chatbot uses Google's AI technology to assist riders in five languages, supporting trip planning, service updates, and feedback via voice or text, with compatibility for screen readers for visually impaired users. By reducing language barriers and providing guided interactions, these tools can make public transportation more usable for non-English speakers and travellers with disabilities. In policy terms, these applications extend beyond convenience and can support equity objectives by enabling a wider range of residents to use shared mobility services with confidence.

# 3. Market Landscape

The global market for AI in automotive and mobility is expanding rapidly, driven by increasing investment, technological advancement, and growing integration of AI across vehicle systems and mobility services. Adoption is accelerating across areas such as ADAS, autonomous driving, and connected mobility platforms, with continued growth expected as technologies mature and scale.

This section outlines key global trends shaping the market, including evolving adoption patterns, investment activity, and commercialization pathways for AI-enabled mobility solutions. It also highlights regional approaches and ecosystem dynamics, providing context for how different jurisdictions are positioning themselves within the emerging AI-driven automotive and mobility landscape.

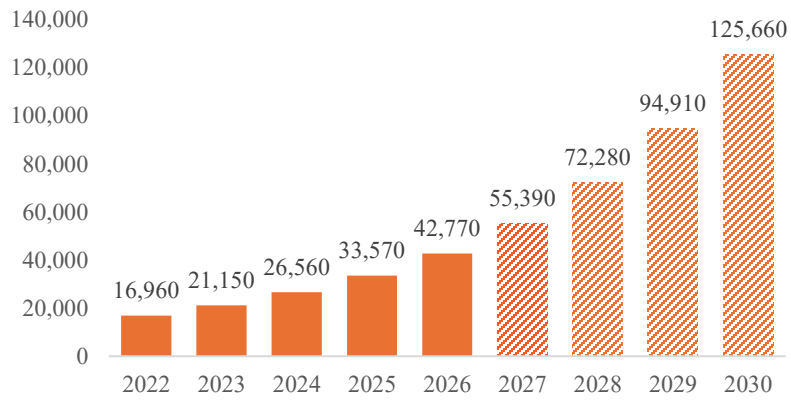
## 3.1 Global AI-Enabled Automotive & Mobility Trends

Worldwide adoption of AI in vehicles is accelerating, supported by strong market growth, increasing deployment, and renewed investment activity. Analysts estimate the global automotive AI market at approximately US$18–$19 billion in 2025, with forecasts suggesting it could more than double by 2030 to US$38 billion in annual revenue. [157] This implies a compound annual growth rate of roughly 15 percent over the second half of the 2020s, driven by the expanding integration of AI across vehicle systems and mobility services.

Growth in market value is being accompanied by rising deployment of autonomous and AI-enabled vehicles. As illustrated in Figure 3, the global fleet of autonomous vehicles is estimated at approximately 43,000 units in 2026, with projections indicating a steeper growth trajectory in the latter part of the decade, reaching around 125,660 units by 2030.[158] While absolute volumes remain modest relative to total vehicle sales, the trend reflects steady progress from pilot deployments toward broader commercialization.

Investment patterns reinforce this momentum. Following a period of weaker venture activity, global funding for mobility technologies increased by approximately US$10 billion in 2024, reaching US$54 billion. [159] This marked the second-highest annual total since 2020. Capital was concentrated in mobility services, sustainable mobility, connected and self-driving solutions, and sales and after-sales, with sustainable mobility attracting the largest share at US$19.6 billion. Renewed investment in connected and self-driving technologies reflects growing confidence in AI-enabled solutions that are closer to market readiness, particularly those aligned with electrification and scalable deployment.

**Figure 3: Global Autonomous Vehicles (Units)**



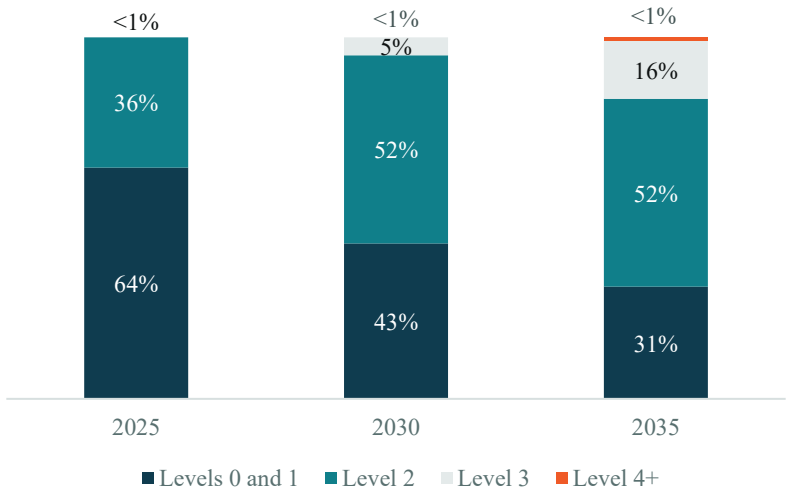

Source: Market.us News, 2026

### Vehicle AI and Autonomy Commercialization Outlook

Commercial adoption of vehicle AI has been strongest in ADAS and related perception capabilities that can be introduced incrementally through successive vehicle releases. Industry projections suggest that vehicles with Level 2 ADAS could account for approximately 52 percent of global new vehicle sales by 2030, supported by regulatory requirements for expanded sensor deployment and declining per-vehicle costs as hardware and software scale across higher production volumes.[160]

Looking further ahead, the share of Level 3 automated driving capable vehicles is projected to increase to approximately 16 percent of sales by 2035, up from less than 1 percent in 2025. This growth is expected to be driven by improvements in software performance, validation processes, and consumer acceptance. Higher levels of automation are likely to remain limited over the same period, with Level 4 and above vehicles estimated to represent around 1 percent of sales by 2035. Figure 4 summarizes projected vehicle sales by level of automation.[160]

**Figure 4: Vehicle Sales by ADAS/AD level**



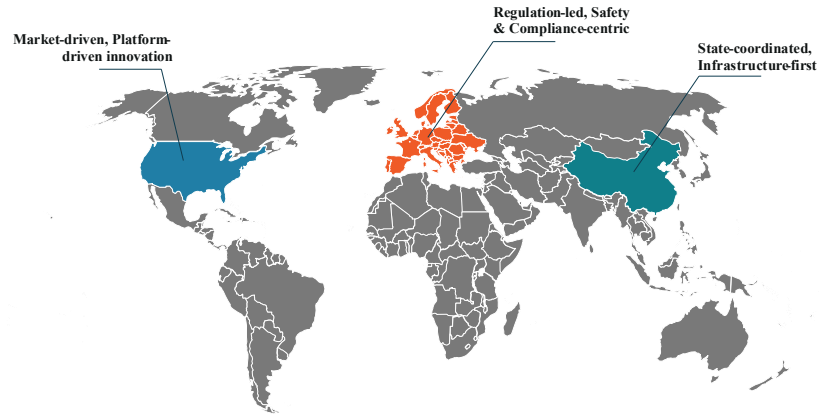

Source: McKinsey & Company, 2026

## Regional AI Adoption Models and Strategic Differences

Geography influences how AI capabilities are developed, governed, and deployed across the mobility sector. Regional approaches reflect differences in policy orientation, industry structure, infrastructure readiness, and public-sector priorities. Rather than listing individual applications, this section summarizes broad adoption models observed in China, Europe, the United States, and selected emerging markets:

- China often follows a state-enabled model that can coordinate large-scale infrastructure and data initiatives (for example, connected corridors with dense sensing).[161] This approach emphasizes vehicle–road–cloud integration and rapid scaling through alignment between government programs, platform providers, and OEMs.

**Figure 5: Regional AI Mobility Deployment Trend**




- Europe tends to adopt a compliance- and assurance-led pathway in which AI-enabled vehicle functions must be supported by a rigorous safety case and aligned with environmental and sustainability requirements. This orientation can extend time-to-market for some features, but it may also strengthen transparency, third-party validation, and conditions for public acceptance.
- The United States is often characterized by a market-led and entrepreneurial model, with innovation driven by technology firms, start-ups, and OEM partnerships. This can support rapid experimentation and early commercialization in selected jurisdictions, but deployment and governance can be uneven where regulatory frameworks vary across states and cities.

In emerging markets such as Southeast Asia, and Africa, AI is frequently applied as an enabling tool to improve mobility system performance (for example, using analytics to improve bus service reliability, incident response, and traffic management) even in contexts where private vehicle ownership remains comparatively low.[162]

## 3.2 Canada's AI Ecosystem: Strengths & Convergence

Canada's strategic position in AI-enabled automobility reflects the overlap of three structural advantages: growing battery and critical minerals ambitions, deep AI research capacity linked to commercialization programs, and an export-integrated automotive sector. Together, these strengths support both domestic adoption and export-oriented growth in applied AI solutions for vehicles, manufacturing, infrastructure, and energy systems. This subsection highlights Canada's AI ecosystem strengths and their convergence with automotive and mobility requirements, with emphasis on commercialization pathways, industrial-scale deployment capacity, and the governance foundations required for safety-critical and connected systems.

### Critical Mineral Advantage

In the shift toward electric mobility, Canada's resource base is a material input to competitiveness. Recent policy and industry activity indicates an effort to connect those resources to downstream battery production and related digital requirements. Canada is a significant producer of critical minerals, such as nickel, cobalt, graphite and lithium, and has set out a Critical Minerals Strategy intended to strengthen participation across the battery value chain, from mining and processing to cell manufacturing, recycling, and second-life applications.[163] As AI adoption accelerates across mining, processing, and battery manufacturing, these minerals-related activities are also becoming data-intensive, creating demand for AI-enabled sensing, optimization, and decision-support tools across the value chain. This creates an opportunity for Canada to link its resource advantage to domestic AI capability by developing and deploying AI solutions that improve productivity, sustainability, and transparency from extraction through to battery deployment.

Battery production and critical mineral supply chains increasingly place greater emphasis on high-quality data, traceability, and verification. As procurement and regulation evolve, battery passports, including material origin, manufacturing emissions, and use history, are becoming an increasingly important mechanism to support compliance, accountability, and market access. In Europe, emerging requirements for battery passports will, by 2027, require many batteries to carry a QR-code-linked record covering materials' origins, $CO_2$ emissions, and compliance with sourcing standards.[163] Canada's Critical Minerals Strategy includes commitments related to traceability technologies intended to support sustainability and ethical sourcing expectations. In August 2024, the industry-led Battery Innovation Roadmap (funded by Natural Resources Canada) similarly called for investment in supply-chain transparency tools to verify origin and ESG conditions of battery inputs.[164]

In addition, Canada is participating in standards and initiatives related to battery traceability and sustainability data. This includes engagement with the Global Battery Alliance's Battery Passport initiative and contributions to emerging standards on material traceability and recycling (ISO 59014). Canadian technology firms are developing systems used for chain-of-custody verification and compliance reporting. For example, Quebec-based OPTEL Group develops supply-chain traceability platforms that can track critical minerals from extraction through battery production and recycling, including the use of AI to support verification and anomaly detection.[165]

### Deep AI Talent and Deployment Experience in Mobility

#### Workforce and Talent

Canada's AI capabilities are well established, particularly in fields that drive automotive and mobility innovation. Early national investment in AI research, including the world's first national AI Strategy in 2017, helped establish three flagship institutes: Mila (Montreal), the Vector Institute (Toronto), and Amii (Edmonton). These institutes have become global hubs for ML, CV, robotics, and optimization research.[166]

Through the Canadian Institute for Advanced Research (CIFAR) AI Chairs program, more than 125 leading researchers are advancing work directly relevant to mobility, including autonomous systems, perception, and safe AI (e.g., advanced ML, CV, and robotics).[166] With Canada hosting 10 percent of the world's top-tier AI researchers,[167] this concentration of expertise provides the technical depth required to solve complex mobility challenges.

Canada pairs research excellence with a strong track record of commercializing AI in regulated, safety-critical domains. Canadian innovations have repeatedly progressed from lab to pilot to real-world deployment in environments requiring high reliability. For example, a collaboration between the University of Ottawa and GM R&D is developing automated verification tools for AI-driven vehicle systems to help ensure that ML components meet strict functional safety standards.[168] More broadly, Canada's AI researchers frequently work with industry on applied assurance challenges. In aerospace and healthcare, two other safety-critical Canadian sectors, AI is being adopted for tasks such as predictive aircraft maintenance and medical image analysis, further demonstrating the ability to meet high regulatory thresholds for safety and efficacy.

### AI-enabled Deployment Experience

Canada has developed mechanisms intended to support commercialization and adoption of AI, including in capital-intensive and safety-critical sectors such as mobility. Recent activity has emphasized collaborative models, including clusters, testbeds, and public–private co-investment, to reduce adoption risk and help solutions move from pilots to operational deployment.

A central element is Canada's network of Global Innovation Clusters, which convene industry, academia, and government around shared technology priorities. In the mobility context, two relevant clusters are SCALE AI (Montreal/Toronto, focused on AI for supply chains) and NGen (Next Generation Manufacturing, including automotive). The Scale AI cluster, supported by federal funding, has funded industry-led AI projects aimed at deployment in operational settings such as factories, warehouses, and transportation systems.[169] Through a co-investment model, it supports consortia where companies and researchers apply AI to operational problems, including logistics optimization and mobility-adjacent infrastructure. In 2025, Scale AI announced $128.5 million for 44 new applied AI projects, including work to automate municipal infrastructure maintenance and optimize public transit and logistics.[170] Recent rounds have reported private-to-public leverage ratios around 2:1, indicating that firms are contributing significant matching investment. The cluster also supports adoption through programming that links AI small and medium-sized enterprises (SMEs) with customers and implementation partners.[170]

In parallel, regional testbeds and demonstration programs provide controlled environments to trial mobility applications. One example is Project Arrow, an all-Canadian EV prototype assembled in 2023–24 by the APMA (Automotive Parts Manufacturers' Association) with funding support from Ontario Vehicle Innovation Network (OVIN).[171] Supported by federal and provincial funding, Project Arrow brought together 50+ Canadian suppliers to build a zero-emission concept vehicle and integrate their technologies into a single platform. The prototype, shown at Consumer Electronics Show 2023, served as a reference case for systems integration, testing, and supplier coordination. APMA has since launched "Project Arrow 2.0", focusing on specific subsystems and commercial prototypes.

Overall, Canada combines AI research capacity with partnerships that support applied deployment in mobility contexts. This combination of technical capability and implementation experience in safety-critical environments can support automakers and mobility operators as they integrate AI into production vehicles, infrastructure systems, and transportation services.

## Global Integration and Market Access

Canada's role in global automotive and mobility markets is shaped by how its AI capabilities are integrated into existing international supply chains, production systems, and infrastructure platforms.

One pathway to integration is as a supplier of AI-enabled systems. Canadian-developed technologies such as BlackBerry QNX, modules produced by Tier 1 suppliers, and AI-enabled sensing and perception solutions are integrated into vehicles assembled in multiple countries. For example, BlackBerry QNX is positioned as a safety-certified platform with a cybersecurity track record that is relevant for OEMs sourcing software components for production vehicles.[172] Canadian Tier 1 suppliers such as Magna also provide AI-enhanced components (e.g., cameras and controllers) that integrate into global OEM supply chains. Investments in AI-enabled automation and quality systems support supplier offerings that OEMs can adopt within established procurement and validation processes.[173]

Canada is also participating in manufacturing intelligence and production analytics. Experience developed in Canadian automotive facilities, such as predictive maintenance, quality analytics, and multi-tier flow optimization, can translate into software products and implementation services for other industrial settings. Where these approaches are documented and validated in operational environments, they can be packaged for adoption by external plants and supplier networks.

Another area is infrastructure analytics and intelligent mobility services. Canadian firms and researchers have participated in smart-city and connected infrastructure deployments, including AI-managed traffic systems and mobility data platforms. For example, Waterloo-based Miovision's computer-vision traffic platform is deployed in many cities. These solutions typically involve analysis of mobility data (traffic flows, transit usage, and EV charging patterns) to support operational decision-making at a municipal or regional level.[174] In EV charging and grid management, Canadian enterprises have developed AI-enabled software to help utilities manage charging demand, drawing on capabilities in power engineering and AI. For market access, these products often need to align with local privacy, cybersecurity, and procurement requirements, which increases the importance of governance and assurance practices.

Canada's integration approach is frequently described as complementary to larger markets, with an emphasis on participation within North American and other partner ecosystems. Canada's 2026 automotive strategy notes that integrated supply chains support global competitiveness.[175] In practical terms, this includes attracting EV and battery investments where Canada provides resources, energy, and R&D capacity, and partnering with international firms that provide manufacturing scale or specialized process know-how. Examples include Canada–South Korea cooperation on future mobility and Canada–EU coordination on battery supply chains.[175] These linkages matter for market access as they connect Canadian capabilities to established distribution, certification pathways, and end customers in external markets.

Overall, Canada's approach to global integration reflects a pragmatic focus on embedding AI capabilities within existing automotive, mobility, and infrastructure systems rather than building end-to-end platforms independently. By supplying safety-critical software, AI-enabled components, manufacturing intelligence, and data-driven mobility services, Canadian firms and researchers align their strengths with established international supply chains and governance frameworks.

# 4. Ontario's Enablers and Adoption Considerations

Ontario has a strong foundation to support the adoption of AI in the automotive and mobility sector, anchored by its advanced manufacturing base, globally recognized AI research ecosystem, and established capabilities in software, sensing, and systems integration. These strengths position the province to participate in the growing AI-driven mobility ecosystem and to capture value across the innovation lifecycle.

This section outlines the key enablers supporting AI adoption in Ontario, including research and talent, infrastructure, and policy frameworks, as well as the broader ecosystem that connects industry, academia, and government. It also highlights the main considerations shaping deployment, including data access, integration complexity, talent availability, and regulatory clarity, which together influence the pace and scale of AI adoption across the sector.

## 4.1 Ecosystem & Capability Foundations

### Ontario's structural assets

Ontario's structural assets are the durable, long-cycle foundations that define the province's capacity to adopt and scale AI-enabled mobility. These include a deep AI talent and research base, a dense industrial supply chain anchored by major OEM assemblers and Tier 1 suppliers, and a cluster of applied research institutions that translate engineering capacity into deployment-ready mobility systems.

### Talent and Research Capability

Ontario's AI ecosystem is anchored by a strong concentration of technical talent within its high-tech corridor. Third-party labour market benchmarks reflect this advantage, with CBRE's 2025 tech talent ranking positioning Toronto as No. 3 among large tech talent markets and highlighting rising demand for AI-specialty talent, including a dedicated AI talent pool of about 24,000 workers. [176] This concentration of talent underpins the province's ability to develop and deploy AI solutions across automotive and mobility applications. This talent base is further reflected in ecosystem growth indicators. Figure 6 shows growth in AI jobs, firm creation, and private investment across Ontario, based on the Vector Institute's 2024–2025 Ontario AI Snapshot. [177] However, the same report highlights a persistent organizational readiness gap, with only 51 percent of companies leveraging AI having organization-wide strategies implemented or in development, which remains a direct constraint on adoption even in a high-talent region.

**Figure 6: Ontario AI Snapshot 2024-25**

Source: Vector Institute, 2025

Building on this talent foundation, Ontario's applied research institutions translate this depth into deployment-ready mobility systems. Table 3 provides some of Ontario's leading universities engaged in AI research for automotive and mobility applications. The institutions highlighted represent the province's largest concentrations of applied research capacity in areas such as autonomous driving, ADAS, smart mobility operations, traffic management, and vehicle validation. Across these universities, research activities span vehicle-level intelligence, system-level optimization, and real-world testing, supported by dedicated laboratories, applied research centres, and deployment pilots. Collectively, these programs contribute to Ontario's ability to develop, test, and transition AI-enabled mobility technologies from research environments into operational and commercial contexts, particularly in safety-critical and infrastructure-integrated applications.

**Table 3: Postsecondary AI and Autonomous Mobility Research Ecosystem Snapshot**

| PSIs | Program/Pilot/Testing |
|---|---|
| The University of Waterloo | The University of Waterloo reports more than 60 dedicated faculty and researchers in connected and autonomous vehicle research. [178] The Autonomous Vehicle Research & Intelligence Lab, opened in 2019, integrates research in perception, mapping, planning, and control for safe autonomy, with a strong focus on real-world testing.[179] Waterloo operates multiple autonomous vehicle platforms, including the Autonomoose self-driving car and the WATonoBus autonomous shuttle, and is widely recognized for advancing autonomous driving in challenging conditions such as snow and ice. Waterloo's work also spans connected vehicles, vehicle cybersecurity, and |

| | |
|---|---|
| | close collaboration with industry to transition research into deployable systems. |
| The University of Toronto | The University of Toronto hosts Canada's largest and most diversified robotics and AI research program through the University of Toronto Robotics Institute. Key labs such as the TRAIL (Toronto Robotics & AI Lab)[180] and ASRL (Autonomous Space Robotics Lab) conduct research in perception, mapping, planning, and control for self-driving vehicles, with an emphasis on robustness in complex urban and winter conditions. At the systems level, the UTTRI (University of Toronto Transportation Research Institute) and CATTS focus on AI-enabled traffic management, transit optimization, and city-scale mobility modeling. The University of Toronto also leads real-world deployment efforts, including the eMARLIN-Transformer AI traffic signal pilot with the City of Toronto and campus-based living labs[181], and supports commercialization through ventures such as Waabi, an autonomous trucking company that has raised US$750 million to accelerate the deployment of its self-driving technology.[182] |
| McMaster University | McMaster University is a major centre for applied research in electric, connected, and autonomous vehicles through the MARC (McMaster Automotive Resource Centre).[183] Research focuses on AI-enabled electric powertrains, intelligent vehicle control, and smart mobility systems, including traffic and transit operations. The AI & Smart Mobility Centre, developed in partnership with Cubic Transportation Systems, applies AI to real transportation operations such as transit optimization and traffic management. Through the MITL (McMaster Institute for Transportation & Logistics) and CITM, McMaster emphasizes industry collaboration and the translation of AI research into tested and deployable mobility solutions.[184] |
| University of Windsor | Situated in Ontario's automotive manufacturing corridor, the University of Windsor focuses on AI applications closely aligned with industry deployment. Through the CARE (Centre for Automotive Research & Education) and the CHARGE Lab, Windsor advances AI-enabled electric motors, power electronics, and vehicle systems.[185] The university is also home to SHIELD, Canada's first dedicated automotive cybersecurity centre, addressing security challenges in connected and autonomous vehicles. Additional work through the AIRC (Autonomous Intelligent Robotics Center) supports autonomous systems and robotics for vehicles and manufacturing, with strong ties to automakers and cross-border transportation use cases.[186] |
| Ontario Tech University | Ontario Tech University specializes in applied automotive and mobility research with a strong emphasis on validation and testing. Its Automotive Centre of Excellence is a unique facility that enables full-vehicle testing under extreme weather, durability, and safety conditions, supporting the development of autonomous and ADAS.[187] Ontario Tech's |

| | |
|---|---|
| | research focuses on robust vehicle control, human–machine interaction, and ensuring AI-enabled vehicle technologies are ready for real-world deployment. The university plays a key role in bridging AI research with commercialization by providing industry-grade testing and certification environments. |

### Industrial and Manufacturing Base

Ontario's industrial base provides material scale and diffusion capacity for mobility AI. In 2024, five OEM assemblers (Ford, GM, Honda, Stellantis, and Toyota) produced more than 1.31 million light-duty vehicles at Canadian plants, the vast majority in Ontario. These assemblers are served by nearly 700 parts suppliers, including globally significant Tier 1 firms such as Magna, Linamar, and Martinrea, and supported by one of the world's only machine-tool-die-and-mould making clusters. Together, these Tier 1 suppliers and advanced manufacturing firms provide the high-precision, automation-ready production capabilities that strengthen Ontario's mobility manufacturing base, with potential to also be adapted to support adjacent defence and security applications as demand and policy incentives evolve.[188] The density of this supplier network creates natural diffusion pathways for validated AI capabilities across manufacturing lines, vehicle electronics, fleet operations, and aftermarket service channels.[189] The province is also consolidating its position in next-generation battery supply chains, illustrated by PowerCo, Volkswagen Group's battery subsidiary, selecting St. Thomas, Ontario for its first North American battery cell gigafactory.[190]

GM maintains a significant AI and autonomous mobility footprint in Ontario through its Canadian Technical Centre cluster in Markham and Oshawa, which serves as one of the company's largest global software engineering hubs.[191] Activities at these centres focus on ADAS, autonomous vehicle software, electrification, and connected vehicle technologies, reflecting the increasing importance of AI-driven software systems in vehicle development. GM is also actively engaged in Ontario-based AI research collaborations, including sponsorship of the University of Toronto's WinTOR autonomous driving initiative, which applies AI and advanced perception technologies to enable vehicle operation in challenging weather conditions such as snow and low visibility.[192]

Ford's presence in Ontario is centred on large-scale manufacturing transformation and integrated software-enabled vehicle production, underpinned by enterprise-wide investments in data and artificial intelligence. The company is investing approximately C$1.8 billion to convert its Oakville Assembly Complex into a high-volume electric vehicle manufacturing hub, incorporating battery assembly and advanced production systems required for next-generation, digitally connected vehicles.[193] Ford maintains a significant Ontario-based R&D footprint through its Connectivity and Innovation Centres in Ottawa, Waterloo, and Oakville, part of a broader C$500 million investment in Canadian research activities supporting more than 500 engineering roles.[194] These centres focus on connected vehicle technologies, including in-vehicle software, infotainment systems, driver-assistance features, and autonomous driving capabilities, with collaboration links to regional talent ecosystems such as the University of Waterloo.

### Digital & Data Infrastructure

Ontario's robust digital backbone underpins AI-enabled mobility. The province hosts multiple cloud computing regions and large-scale data centres, supporting local access to high-performance computing and data storage required for AI development and deployment. A notable signal of this capacity is Microsoft's multi-billion-dollar investment to expand AI cloud infrastructure in Ontario, delivered as part of a broader $19 billion Canada-wide commitment.[195] This includes new data centre capacity designed to support large-scale AI and advanced data processing workloads. This expansion is reinforced by Ontario's clean

and reliable electricity system, which strengthens the province's position as a location for energy-intensive AI operations. Ontario's electricity mix, dominated by nuclear and hydro generation, allows data centres and AI infrastructure to operate at scale with a comparatively low carbon footprint. This combination of compute availability and reliable low-emissions power is increasingly important as AI workloads grow in size and energy demand.

The expansion of data centres and AI infrastructure introduces emerging system considerations. Concentrated electricity demand from large-scale facilities can place localized pressure on substations, transmission corridors, and grid connection timelines.[196] While data centres currently represent a relatively small share of overall electricity consumption, rapid growth may create infrastructure bottlenecks if grid capacity and planning processes do not keep pace. This highlights the importance of coordinated energy system planning to ensure that new demand can be integrated efficiently without impacting system reliability.

Ontario's connectivity infrastructure further supports AI-enabled mobility. Through public–private partnerships such as ENCQOR 5G, Ontario and Québec established a 5G testbed corridor that enables companies to develop and trial ultra-fast, low-latency communications for connected vehicles and smart infrastructure applications.[197] This environment supports experimentation with advanced use cases that depend on deterministic performance, including connected vehicle services, infrastructure sensing, and real-time system coordination.

These digital highways (ubiquitous high-speed wireless, fibre-optic networks, and edge computing nodes) form a structural asset by enabling real-time vehicle-to-cloud services, OTA updates, and city-wide sensing that are all prerequisites for AI-driven mobility at scale. Together, strong cloud/edge infrastructure and reliable power supply ensure that Ontario-based mobility AI innovations have the computing resources and connectivity they need to deploy broadly.

### Semiconductor, Electronics & Software Ecosystem

Ontario has developed a substantial base of semiconductor, automotive electronics, and embedded software capability that supports AI-enabled mobility. Global chipmakers and specialist suppliers are expanding their presence in the province. Marvell Technology, a firm focused on data infrastructure semiconductors, is investing $238 million over five years to expand research and development activities in Ottawa and Toronto. This investment includes a new optical semiconductor laboratory and is expected to add up to 350 high-skilled jobs. More broadly, Ontario's technology corridor employs over 430,000 workers across approximately 25,000 firms and includes specialized chip design centres and research and development operations for companies such as AMD in Markham and Synopsys in Ottawa.[198]

Ontario is also home to BlackBerry QNX, based in Ottawa, which is a leading provider of automotive operating system software. QNX's real-time operating system is embedded in more than 275 million vehicles globally and provides safety-certified platforms for advanced driver assistance and in-vehicle infotainment systems.[199] This reflects Ontario's role within the global automotive technology supply chain, particularly in software layers that support safety-critical vehicle functions.

Publicsector investment and industrial policy are reinforcing this ecosystem. Through Invest Ontario, the provincial government has co-funded semiconductor and electronics expansions, including grant support for Marvell, and has identified microelectronics and AI chips as strategic priorities.[200] This combination of chip research and development, embedded software expertise, and policy support positions Ontario as a contributor to the design, integration, and validation of next-generation vehicle intelligence systems, rather than vehicle assembly alone. The presence of both hardware and software capabilities supports sustained adoption of AI across automotive and mobility applications.

## Logistics, Freight & Trade Corridors

Ontario's physical transportation networks function as structural enablers for AI adoption in freight and fleet operations. The Ambassador Bridge between Windsor and Detroit alone carries approximately 25 percent of total Canada–U.S. trade by value, making it the busiest commercial land border crossing on the continent.[201] When combined with traffic across the Sarnia Blue Water Bridge, a concentrated corridor in southwestern Ontario experiences a high volume of automotive and industrial freight movement.

This concentration of predictable, just-in-time truck traffic creates favourable conditions for the deployment of AI-enabled logistics applications. These include fleet coordination, traffic management systems that reduce congestion and delay at border crossings, and early trials of connected or automated trucking technologies in cross-border environments. Ontario has also invested in upgrading key trade routes. The Gordie Howe International Bridge, scheduled to open in the 2025–26 period, is expected to expand capacity at the Windsor crossing and introduce modern inspection facilities and digitally enabled infrastructure that can support connected corridor technologies within a trade and customs context.[202]

Beyond international gateways, Highway 401 serves as Ontario's primary east–west freight artery, linking Windsor, London, the Greater Toronto Area, and eastern Ontario. Portions of the highway carry traffic volumes of up to approximately 400,000 vehicles per day within the Greater Toronto Area (GTA).[203] The density and consistency of freight movement along this corridor create opportunities for AI applications such as route optimization, congestion forecasting, and infrastructure condition monitoring.

Ontario's logistics system also includes major multimodal hubs. Toronto Pearson International Airport is Canada's largest airport and a key air cargo gateway. Hamilton Port supports the movement of steel and automotive materials, and large rail intermodal terminals in locations such as Brampton and Vaughan handle containerized freight. These nodes generate large volumes of operational data related to traffic flows, shipments, and asset utilization, which can support AI-driven analysis and efficiency improvements.

Public-sector engagement reinforces this environment. Provincial and regional initiatives that focus on freight efficiency, including research and coordination activities associated with the Smart Freight Centre in the GTA, indicate institutional readiness to adopt AI tools to improve goods movement.[204] The scale and connectivity of Ontario's freight and trade infrastructure concentrate relevant use cases and operational users, supporting the application of AI across trucking, logistics, and transportation network management.

## Public-Sector Anchors & Demand Drivers

Ontario's public sector plays an enabling role in the adoption of AI across automotive and mobility systems. Provincial ministries, municipal governments, and large transit agencies act as early users of digital technologies and provide operational environments where new solutions can be tested, refined, and scaled. Through procurement activities, policy direction, and access to real-world assets, public agencies contribute to the maturation of AI-enabled mobility technologies.

A central example is the Ontario's Ministry of Transportation's COMPASS traffic management system, which actively manages highway operations across the Greater Toronto Area. The system integrates hundreds of freeway cameras, electronic message signs, traffic detectors, and a continuously staffed control centre. This infrastructure generates operational data that is made available through platforms such as Ontario 511 and the provincial open data portal.[205] AI developers and researchers can use these datasets to train and validate models for applications including incident detection, congestion forecasting, and route optimization. The widespread instrumentation of road networks and the availability of data support ongoing AI

development in live operational settings.

Public-sector policy and procurement also influence demand for AI-enabled solutions. Initiatives related to fleet electrification, road safety targets, and traffic performance standards create requirements that can be addressed through digital tools such as intelligent charging management systems and vision-based safety technologies for transit vehicles. These policy-driven requirements help establish a market for applied AI solutions that address operational and regulatory objectives.

Collaboration between public agencies and research institutions further supports this environment. Ontario municipalities and transit authorities regularly partner with universities and technology developers on applied research and pilot projects. One example is the City of Toronto's collaboration with the University of Toronto on AI-based traffic signal control systems, mentioned above. These forms of engagement, including data access, pilot deployments, and public procurement, enable AI mobility solutions to be tested with real users and real constraints within Ontario's public services.

## Ontario enabling programs and corridor-scale testbeds

### Ontario Piloted Programs

Ontario's adoption model relies on translating research and early prototypes into real-world pilots, then into repeatable deployments. OVIN serves as the connector across this ecosystem, with an expanded mandate that explicitly targets the translation of Ontario-made technologies into global markets, making it a natural vehicle for facilitating AI mobility applications from proof-of-concept into repeatable commercial deployment.[206]

- **Automated Vehicle Pilot Program**

Ontario's Automated Vehicle Pilot Program (AVPP) is a provincially regulated framework that enables the testing of connected and automated vehicles on public roads under defined safety and oversight conditions.[207] Launched on January 1, 2016, the program made Ontario

## Case Study: Kiwi Charge

**Autonomous EV Charging Project**

Limited charging access and operational constraints remain barriers to electric vehicle adoption, particularly for fleet and shared mobility applications where vehicles must remain in service for extended periods. To address this, Kiwi Charge is piloting an autonomous AI-enabled mobile charging solution that enables electric vehicles to be charged without manual intervention, reducing downtime and improving asset utilization.

Launched in February 2026 and supported by $1.7 million in funding, the pilot focuses removing the need for fixed charging stations or manual plug-in processes by deploying AI-enabled robotic charging systems capable of navigating to parked vehicles and connecting them to charging infrastructure.

The pilot is designed to validate the operational feasibility of autonomous charging in real-world environments, including reliability, safety, and integration with fleet operations. By enabling on-demand, flexible charging, the project aims to support higher utilization of electric fleets and reduce infrastructure constraints that can limit electrification at scale.

This pilot highlights the potential role of autonomous charging systems as an enabling layer within the EV ecosystem, offering a pathway to more flexible and scalable charging models, particularly in urban, fleet, and high-utilization mobility contexts.

Source: Kiwi Charge Inc., 2026

the first Canadian jurisdiction to formally regulate on-road testing of automated vehicle technologies. The regulatory framework was updated in January 2019 to reflect technological progress, allowing driverless automated vehicle testing and cooperative truck platooning under specific safety requirements, while excluding production-ready SAE Level 3 vehicles eligible for sale in Canada from the pilot. Since 2016, the pilot has allowed participating organizations to collect data, demonstrate technology, and build partnerships in Ontario.[207] The Ministry of Transportation of Ontario continues to monitor emerging research and best practices and to adjust the pilot framework as needed to support innovation and economic growth while maintaining road safety.

- **Cooperative Truck Platooning Pilot Program**

Ontario's Cooperative Truck Platooning Pilot Program is a provincially administered initiative that supports real-world testing of connected and partially automated trucking technologies under defined regulatory and safety conditions.[208] The program enables approved commercial operators to deploy platoons of trucks equipped with ADAS and vehicle-to-vehicle communication, allowing vehicles to operate in coordinated formations while maintaining human driver oversight in each vehicle. Testing is limited to designated highway corridors and subject to specific participation requirements, including operator approvals, driver qualifications, and operational constraints. The pilot is intended to generate performance and safety evidence on how platooning technologies function in live traffic environments, informing broader adoption decisions and contributing to Ontario's approach of scaling mobility innovations through controlled, corridor-based testing and deployment.

- **QEW Innovation Corridor Program – Smart Mobility and Connected Vehicle Pilots**

Ontario has designated a 40-km stretch of the Queen Elizabeth Way (QEW) between Burlington and Toronto as the QEW Innovation

## Case Study: Global Sensor Systems Inc.

**AI-Based Fleet Safety Systems**

Commercial fleet operations face persistent safety risks, particularly in low-speed reversing scenarios where limited visibility and dense operating environments increase the likelihood of collisions. Global Sensor Systems, in partnership with OMS Express, has developed a potential solution in the form of SecurePath™, an AI-enabled automatic reverse braking system designed to reduce backing accidents in commercial fleet operations.

Supported by the Ontario Vehicle Innovation Network (OVIN), the project combines public and private investment to advance the development and validation of this system. SecurePath™ integrates multiple sensor technologies, including LiDAR, time-of-flight sensors, and digital cameras, alongside AI-based sensor fusion to monitor vehicle surroundings and generate predictive alerts. The system can also automatically apply braking in reverse scenarios, with configurable settings tailored to different fleet operating conditions.

The platform incorporates adaptive features such as memory-based learning, enabling it to recognize recurring environments and reduce false warnings over time. This supports more consistent and reliable performance in operational settings where vehicles frequently operate in constrained or repetitive environments.

SecurePath™ highlights the potential for AI-enabled, sensor-integrated safety systems to address common operational risks in commercial fleets. By improving situational awareness and enabling automated intervention, such technologies provide a pathway to reducing accidents, enhancing worker safety, and supporting more standardized safety practices across fleet operations.

Source: Global Sensor Systems, 2025

Corridor, a living lab where Ontario-based companies can deploy and test connected and autonomous vehicle technologies in real-world highway conditions. Through the QEW Innovation Corridor program, administered by OVIN as a co-investment fund, cohorts of SMEs receive up to $150,000 in funding, with nine companies selected in the first intake to pilot solutions in areas including queue warning systems, work zone safety, predictive traffic management, and in-vehicle traveller information.[209] The program features two challenge-based funding streams alongside an open call: the Work Zone Safety stream focuses on real-time tracking of lane closures and detecting activities in work zones, while the Queue Warning stream supports innovative approaches beyond conventional systems, including predictive algorithms, edge computing, and alternative motorist advisory methods.[210]

### Testing, Standards & Validation Infrastructure

Complementing the corridor, OVIN's Technology Pilot Zones provide a second scaling pathway focused on integrating SME solutions into real environments with co-investment. Launched in February 2024 with an $8-million federal investment delivered through FedDev Ontario, the program establishes two world-class, live-environment pilot zones in Toronto and Windsor/Sarnia. Together, these sites are expected to support more than 40 small and medium-sized enterprises as they pilot and commercialize over 40 new technologies, predominately in the zero-emission vehicle and connected and autonomous vehicle domains.[211] Under a common program structure that applies across all sites, eligible SMEs can receive up to $100,000 in co-investment over a maximum of 24 months, provided on a 1:1 private-sector matching basis.[212]

The Toronto zone is designed as an urban testbed enabled by 5G wireless connectivity and leading-edge computing infrastructure, including AI-based traffic management technologies.[213] OVIN has since partnered with the Toronto Transit Commission (TTC) to allow Ontario companies to pilot transit solutions directly within the TTC network, including buses, stations, and supporting infrastructure.[214] In parallel, the Windsor/Sarnia zone focuses on cross-border and multimodal scenarios, providing a launch pad for pilots in real-world environments such as highways and cross-border sites to improve the safe and efficient movement of people and goods.[215] These zones build on existing demonstration sites in Vaughan's Metropolitan Centre and Markham's Centre, where SMEs can integrate solutions with municipal assets such as streetlights and smart controls, traffic signals and signage, and EV charging stations. This is an important consideration because many AI-enabled mobility use cases require integration across sensing, connectivity, and municipal systems, not only in-vehicle software.[216]

An often under-recognized asset is Ontario's capacity for safety testing, certification, and tech validation in mobility. Deploying AI in vehicles and infrastructure requires rigorous validation, and Ontario hosts specialized facilities to do just that. One centerpiece is Area X.O in Ottawa (formerly the Ottawa L5 site) – a first-of-its-kind integrated test facility in North America for autonomous vehicles and smart city tech. This secure 1,866-acre site offers a private test track and a fenced proving ground equipped with cutting-edge telecom (4G/5G, IoT networks), smart intersections, and even a drone zone. It allows companies to test driverless cars, delivery robots, V2X (vehicle-to-everything) communications, and more, under controlled yet realistic conditions. FedDev Ontario's $7 million investment in Area X.O (2020) further upgraded its capabilities with a cybersecurity innovation lab (to probe and harden AI systems against cyber threats), an on-site additive manufacturing lab for rapid prototyping, and a mobile command centre that can deploy connectivity to rural test locations. The presence of this facility means Ontario-based AI developers don't have to leave the province to validate safety and performance – they have a world-class test range at hand. In terms of standards and certification, Ontario benefits from organizations like Canadian Standard Associated (CSA) Group's Toronto labs, which test and certify automotive

electronics and charging equipment to global safety standards, and Transport Canada's Motor Vehicle Test Centre (though located in Quebec) which Ontario companies can access for crash and safety testing. Moreover, Ontario's leading role in AV pilot regulation (first in Canada) means the province's officials and local experts are helping shape the safety frameworks – effectively building "soft infrastructure" of know-how in safety assurance for AI mobility. All these elements – test tracks, labs, and standards expertise – form a structural mosaic ensuring that AI innovations can be proven out and de-risked in Ontario before wider deployment. This validation ecosystem is critical for turning prototypes into trusted, market-ready products in the mobility sector.

## 4.2 Deployment & Adoption Readiness

Deployment and adoption readiness in Ontario is best understood as staged maturity and risk reduction, rather than a single go-live event. OVIN's Regional Technology Development Sites (RTDS) are the primary mechanism for this, supporting SMEs through the development, testing, prototyping, validation, and commercialization of automotive and smart mobility solutions, while providing access to specialized equipment, hardware, software, and business and technical advisory services.

The RTDS model is explicitly structured to reduce barriers to innovation by connecting SMEs with post-secondary institutions, regional innovation centres, incubators and accelerators, industry partners, and municipal and regional resources in a single, co-located network. This multi-stakeholder architecture matters for AI-enabled mobility in particular, where solutions typically require integration across vehicles, infrastructure, data systems, and municipal operations, and where risk reduction at the development and validation stage is a precondition for repeatable commercial deployment.[217]

On February 6, 2026, OVIN announced the expansion of the RTDS network to nine sites under its renewed mandate, backed by $17.5 million in OVIN investment, $32.8 million in matching industry investment, and over $19.3 million from the broader public sector, for a total of over $69.6 million. The nine sites span Durham, Hamilton, Kingston, Northern Ontario, Ottawa, Simcoe County, Waterloo, Windsor-Essex, and York Region. Each site focuses on distinct aspects of the automotive and smart mobility sector such as hardware, security, data analytics, electrification, and connected systems.[218]

The York Region RTDS provides a concrete illustration of how the model is operationalized for AI and connected mobility. Delivered through York University's YSpace and ventureLAB, it explicitly supports SMEs in progressing through Technology Readiness Levels (TRL) 1 to 7, with automotive AI, smart mobility, electrification, and connected and autonomous vehicle technologies as named focus areas. Available support includes access to prototyping labs, real-world municipal testing infrastructure through York Region's dark fibre network and fleet vehicles, and commercialization programming targeting OEM and industry validation partnerships.[219] This TRL-structured approach signals the RTDS network's intent to bridge the gap between research prototypes and operationally validated deployments ready for scale.

## 4.3 Regulatory Framework

Ontario's regulatory posture combines formal on-road pilot rules with programmatic testbeds that function as de facto sandboxes. This enables experimentation while maintaining safety, liability, and public trust as the primary constraints. In operational terms, the regulatory question is not only whether an AI system performs technically, but also how responsibility, risk, and legitimacy are distributed between developers, operators, municipalities, and the public.

At the legal baseline, Ontario Regulation 306/15 under the Highway Traffic Act prohibits anyone from driving or permitting the operation of an automated vehicle on a highway unless that operation is authorized under the regulation.[220] To create a controlled exception to this default

rule, Ontario established the AVPP, as discussed above. This approach reflects a broader pattern in which controlled trials and pilot frameworks mediate between fast innovation cycles and public safety expectations, enabling learning under real-world constraints while keeping participation scoped and auditable.

Ontario has extended this experimentation model into freight and heavy vehicle contexts. The province launched a ten-year Automated Commercial Motor Vehicle (ACMV) Pilot Program running from August 1, 2025 to August 1, 2035, structured to allow approved carriers to test automated commercial vehicles weighing more than 4,500 kg and equipped with SAE Level 3, 4, or 5 automation on Ontario roads. The program operates across two streams: a driver-supervised stream where a qualified driver remains ready to take control, and a driverless stream where a remote or in-vehicle assistant monitors operations. [221] Commercial vehicle operations introduce distinct risk profiles related to vehicle mass, operating hours, and interjurisdictional corridors, and the ACMV program's approval and reporting requirements are therefore designed to generate the performance and safety evidence needed to inform governance frameworks applicable across mobility AI.

Ontario's experimentation posture also extends into adjacent infrastructure domains. The Ontario Energy Board's Innovation Sandbox, launched in 2019, provides regulatory guidance to utilities and companies seeking to test new services and business models. In one relevant case, the Sandbox assisted Alectra in understanding how its AlectraDrive @Home residential EV charging pilot was consistent with regulatory requirements, enabling the project to proceed and generate insights on EV charging behaviour and grid impacts.[222] For AI-enabled mobility, this cross-regulator sandbox behaviour is relevant because deployment increasingly depends on coordinated vehicle, charging, energy, and municipal data systems, not vehicle technology alone.

Alignment with national safety and public acceptance expectations remains a central constraint across all of these mechanisms. Transport Canada published Canada's Safety Framework for Connected and Automated Vehicles 2.0 in February 2025, describing the federal government's safety-focused approach to connected and automated vehicle technologies and clarifying the roles and responsibilities of different orders of government in approving and facilitating trials. The framework reinforces that provincial experimentation must remain interoperable with federal oversight, safety evidence requirements, and public confidence considerations.[223]

This progression illustrates how Ontario’s approach has evolved from early, tightly scoped on-road testing toward broader experimentation that includes freight operations and energy-adjacent enabling systems. Collectively, these steps reflect a shift toward staged adoption: pairing pilots with clearer approval conditions, cross-regulator coordination, and alignment with national safety guidance to support public trust and repeatable deployment.

**Table 4: Ontario Policy and Pilot Milestones for Automated and Connected Mobility**

| Year | Milestone |
|---|---|
| 2016 | AVPP begins and Ontario becomes the first Canadian jurisdiction to regulate AV testing on public roads under O. Reg. 306/15, establishing a formal pathway for auditable, evidence-generating trials. |
| 2019 | AVPP updated to permit driverless AV testing and cooperative truck platoons under specified conditions, expanding the scope of sanctioned experimentation. |
| 2019-Present | OEB Innovation Sandbox enables regulated utilities to test new services; assists EV charging |

| | |
|---|---|
| | pilots such as AlectraDrive @Home (launched 2020), generating evidence on charging behaviour and grid impacts as electrified mobility scales. |
| 2025-2035 | ACMV Pilot Program (August 1, 2025 to August 1, 2035) extends structured experimentation into higher-risk freight contexts, with two testing streams and carrier approval requirements designed to generate safety and performance evidence. |
| February 2025 | Transport Canada publishes Safety Framework for Connected and Automated Vehicles 2.0, clarifying federal-provincial roles and reinforcing that scaling depends on consistent safety evidence, transparent accountability, and public acceptance |

## 4.4 Dual-Use Enablers

As the Canadian government seeks to balance domestic economic growth with expanding national security and defence commitments, capital needs to be deployed strategically to maximize both economic and security outcomes. Dual-use technologies offer a particularly effective path forward. Automotive AI is inherently dual-use, as the core capabilities that support commercial mobility, including intelligence, cyber-physical security, and autonomous systems, are also foundational to modern defence applications. Advancing the commercial automotive AI ecosystem simultaneously strengthens Canada's defence industrial base, ensuring domestic R&D generates both economic and security benefits.

Ontario's civilian mobility and manufacturing ecosystem is increasingly complemented by federal and provincial frameworks that explicitly target dual-use and defence-relevant technologies. At the federal level, the Regional Defence Investment Initiative (RDII) establishes a 357.7-million-dollar national envelope to support Canada's defence and security needs while strengthening regional economic development. Delivered through regional development agencies, RDII is mandated to accelerate the integration of businesses and ecosystems into domestic and international defence supply chains and to increase their industrial and innovation capacity.[224] In Southern Ontario, FedDev Ontario receives more than 90 million dollars under RDII and has committed an additional 106 million dollars from its existing resources, bringing total regional defence support to nearly 200 million dollars.[225] RDII guidance explicitly identifies dual-use firms as priority beneficiaries, including those in artificial intelligence, cybersecurity, quantum technologies, sensors, land vehicles, and uncrewed and autonomous systems. For Ontario-based AI and mobility companies that are already maturing technologies through OVIN, RTDS, and corridor-scale pilots, RDII provides a clearly signposted federal pathway into defence supply chains.

Provincial policy is beginning to mirror this dual-use emphasis. Ontario's 2025 budget announced an additional 90 million dollars in venture capital funding through Venture Ontario, including a 50-million-dollar carve-out for Ontario-based Venture Capital funds focused on technologies that support national defence, artificial intelligence, and cybersecurity. This allocation is framed as a measure to support next-generation technologies, enhance provincial competitiveness, and strengthen economic resilience.[226] In effect, it creates a dedicated risk-capital channel for Ontario companies developing AI, autonomy, and security technologies with potential defence and national-security applications, complementing RDII's project- and ecosystem-level funding.

## 5. Opportunities for Ontario

AI presents a range of strategic opportunities for Ontario across the automotive and mobility sector, particularly in areas where the province has established strengths in advanced manufacturing, applied AI research, and systems integration. As the sector continues to evolve toward connected, software-defined, and service-based mobility, Ontario is well positioned to capture value across both technology development and deployment.

This section highlights key opportunities for Ontario to strengthen its role in the AI-driven mobility ecosystem, including accelerating commercialization, scaling high-impact use cases, and supporting industry collaboration. It also outlines areas where targeted focus and coordination can enable the province to build competitive advantage and drive long-term economic and innovation outcomes.

### 5.1 Scaling AI-Enabled Mobility Deployment in Targeted Use Cases

Ontario has a near-term opportunity to scale AI through specific, high-value mobility applications where operational benefits and demand are already evident. These include freight logistics, autonomous trucking, fleet operations, and smart infrastructure systems, with the greatest impact expected where deployments are anchored in clearly defined use cases and developed in partnership with end users.

Interview insights highlight that autonomous and AI-assisted logistics represent one of the most immediate opportunities. High-frequency, short-haul routes between warehouses, distribution centres, and retail locations are particularly well-suited to automation, as they offer predictable operating conditions and strong economic incentives tied to labour shortages, cost reduction, and efficiency gains. Deployment in these environments allows Ontario to move beyond pilot programs toward real-world operations while building public familiarity and trust in AI-enabled systems.

Similarly, AI-driven fleet management and infrastructure optimization present opportunities to improve system-wide performance. Applications such as predictive maintenance, real-time routing, and traffic optimization can deliver measurable benefits across public transit, municipal operations, and commercial fleets. These use cases allow Ontario to demonstrate tangible value from AI while improving safety, reliability, and service delivery.

Ontario's existing programs, such as the Technology Pilot Zones, provide a foundation for this approach by enabling industry-led testing and deployment anchored in defined use cases. Expanding this model can support the transition from pilot to broader deployment by connecting solution developers with end users and real-world environments where adoption can scale.

### 5.2 Leveraging Ontario's Manufacturing Base for AI-Driven Production and Systems Integration

Ontario's established automotive and advanced manufacturing ecosystem creates a strong foundation for AI integration across the production lifecycle. This positions the province to lead not only in AI adoption, but in embedding AI within globally competitive manufacturing systems.

AI-enabled smart factories, robotics, and digital twins are already transforming production processes, enabling predictive maintenance, quality inspection, and real-time operational optimization. Ontario's strength lies in its ability to integrate these capabilities into existing manufacturing networks, including OEMs, suppliers, and technology providers.

Beyond factory applications, there is a growing opportunity in systems integration and software-defined vehicles, where AI capabilities are embedded directly into vehicle platforms. As vehicles become increasingly software-driven, value is shifting toward data, analytics, and continuous updates. Ontario-based firms can capture this value through development of onboard AI systems, edge computing solutions, and vehicle data platforms, and by leveraging programs such as OVIN incubators to connect with OEMs, integrate into supply chains, and scale their solutions globally.

This opportunity extends to the broader supply chain, where Ontario companies can participate in global markets by providing AI-enabled components, platforms, and integration services rather than solely physical manufacturing.

### 5.3 Strengthening Ontario's Position in AI Development, Data, and Digital Platforms

Ontario's strong talent base and research ecosystem create opportunities to lead in AI development, data utilization, and digital infrastructure for mobility systems.

Stakeholders emphasized that data is becoming a critical competitive asset. The ability to collect, process, and analyze large-scale mobility data, including vehicle, infrastructure, and operational data, enables

advanced AI applications such as digital twins, predictive analytics, and real-time decision-making. Ontario is well positioned to build platforms that transform raw data into actionable insights for both public and private sector use.

In particular, emerging applications such as real-time road intelligence, infrastructure monitoring, and mobility system optimization represent new market opportunities. These solutions extend beyond automotive into municipal planning, safety, and infrastructure management, allowing Ontario to develop cross-sector AI capabilities with export potential. Supporting commercialization of these opportunities will require leveraging Ontario's pilot programs and testbeds, access to public-sector data systems, and partnerships with municipalities and industry to validate solutions in real-world settings and scale them across the mobility ecosystem.

At the same time, Ontario's research institutions and programs provide a steady pipeline of AI talent. Strengthening pathways between academia and industry, including commercialization and applied research, will be critical to converting this advantage into sustained economic value.

### 5.4 Enabling AI Deployment through Regulation, Standards, and Trust

A consistent theme across interviews suggests that regulatory clarity and public trust are central to unlocking AI adoption. Ontario has an opportunity to position itself as a leading jurisdiction for safe and responsible deployment of AI-enabled mobility technologies.

Stakeholders highlighted that regulatory frameworks are currently evolving and often lag technological capabilities. Establishing clear guidelines for safety validation, liability, and system performance would accelerate deployment by reducing uncertainty for industry and investors. This is particularly important for autonomous vehicles and other safety-critical applications, where deployment depends on rigorous assurance and compliance. Related to this, there is an opportunity to develop standardized evaluation and testing frameworks for AI systems. Consistent benchmarks and validation processes would improve reliability, enable comparability across solutions, and support commercialization.

Public trust also remains a critical factor. Increasing transparency, improving communication around safety, and demonstrating real-world performance will be essential to broader acceptance. Early deployments in controlled or well-understood environments can play a key role in building confidence and familiarity.

### 5.5 Unlocking Collaboration and Data-Sharing Models Across the Ecosystem

AI deployment in mobility requires coordination across multiple stakeholders, including government, industry, technology providers, and research institutions. Ontario has an opportunity to build collaborative models that accelerate innovation.

Interview insights point to the importance of shared infrastructure, including testbeds, simulation environments, and data platforms. These resources allow organizations to validate AI systems more efficiently while reducing individual costs and risk. Existing programs, such as OVIN RTDS, and Technology Pilot Zones, facilitate collaboration between SMEs and larger players and are particularly valuable in supporting ecosystem growth. In addition, stakeholders identified opportunities for data and intellectual property sharing, particularly where there is broader public value, such as accessibility, safety, or infrastructure optimization. However, these models require appropriate incentive structures to ensure participation from private-sector organizations.

As AI-enabled mobility scales, greater clarity on the roles and responsibilities of key stakeholders will become increasingly important to support coordinated deployment. While Ontario's ecosystem already brings together automakers, utilities, charging providers, technology developers, and regulators, more explicit delineation of how each actor

contributes to system design, integration, and operations can reduce duplication, improve accountability, and support more efficient implementation.

Expanding collaboration across sectors, including transportation, energy, and urban infrastructure, further enhances Ontario's ability to develop integrated AI solutions that address system-level challenges rather than isolated use cases.

### 5.6 Advancing AI-Enabled Energy Integration and Grid Flexibility

Ontario has an opportunity to more fully integrate AI-enabled mobility within broader electricity system planning, positioning EVs, charging infrastructure, and distributed energy resources as active components of the energy system. As electrification accelerates, these assets can support peak demand management, improve load balancing, and align electricity consumption with available generation. Strengthening this integration will require greater consideration of system-level factors, including infrastructure readiness, distribution system constraints, and long-term electricity demand planning.

Building on Ontario's strong foundation of pilot projects and innovation programs, there is an opportunity to define pathways for scaling these solutions to broader deployment. Moving beyond demonstration environments will require coordinated implementation across fleets, charging networks, and utilities, as well as the ability to manage increasing operational complexity, such as real-time load management and geographically distributed demand. Expanding enabling mechanisms, including demand response programs, dynamic pricing, and DER aggregation models, can support this transition by creating clearer value streams for flexible participation.

As deployment increases, interoperability across vehicles, charging infrastructure, and electricity systems will be essential to ensure seamless system operation. Advancing common standards, data-sharing frameworks, and system interfaces can improve coordination across stakeholders, enhance system visibility, and reduce integration challenges as solutions scale across jurisdictions and asset types.

### 5.7 Further Strengthen Industry and Academic Integration

Ontario's AI ecosystem is anchored by globally recognized research institutions. Interviews indicated that while Ontario has strong programs in place to support collaboration, there remains an opportunity to further strengthen connections between academic innovation and industry adoption

There is an opportunity to strengthen collaboration mechanisms that translate research into deployed solutions, particularly in manufacturing, autonomous systems, and mobility operations. Expanding applied research partnerships, co-op programmes, and demonstration environments can help ensure that AI breakthroughs developed within Ontario are commercialized locally rather than migrating to other jurisdictions.

Deepening these linkages would allow Ontario to retain intellectual property, accelerate product development cycles, and support the growth of domestic firms across the AI mobility value chain.

### 5.8 Scaling Commercialization and Global Competitiveness

Finally, Ontario's long-term opportunity lies in transitioning from innovation to commercialization and global market participation.

While the province has strong capabilities in research and early-stage development, stakeholders noted that scaling companies and retaining talent remain persistent challenges. Strengthening commercialization pathways, including access to capital, customers, and international markets, will be critical to sustaining long-term growth.

Export opportunities are emerging in AI-enabled mobility technologies, particularly in areas such as autonomous systems, fleet management platforms, and smart infrastructure solutions. Ontario-based companies can leverage domestic deployments as proof points to strengthen their competitiveness in international markets. Programs such as OVIN's Going Global initiative can further support this growth by helping

Ontario companies enter new markets, integrate into global supply chains, and scale cutting-edge technologies across key international jurisdictions. Facilitating market access can help Ontario firms expand their global footprint while reinforcing the province's position as a hub for automotive and mobility innovation. At the same time, reinforcing the broader innovation ecosystem, including increasing risk tolerance and investment in scaling startups, can help ensure that successful companies grow and remain within the province.

Taken together, Ontario's opportunity is not limited to any single technology or application. Rather, it lies in the province's ability to integrate AI across the broader mobility ecosystem, from manufacturing and vehicles to infrastructure and services. By prioritizing targeted deployment, leveraging existing industrial strengths, enabling regulatory clarity, and supporting commercialization, Ontario can position itself as a leading jurisdiction for AI-enabled automotive and mobility systems.

# 6. Glossary

| | |
|---|---|
| ACMV | Automated Commercial Motor Vehicle |
| AD | Automated Driving |
| ADAS | Advanced Driver Assistance Systems |
| AI | Artificial Intelligence |
| BMS | Battery Management System |
| CNN | Convolutional Neural Network |
| CV | Computer Vision |
| EV | Electric Vehicle |
| GM | General Motors |
| GPS | Global Positioning System |
| GTA | Greater Toronto Area |
| HIL | Hardware-in-the-Loop |
| IEC | International Electrotechnical Commission |
| IATA | International Air Transport Association |
| IOT | Internet of Things |
| ISO | International Organization for Standardization |
| LKAS | Lane Keeping Assist System |
| MAAS | Mobility as a Service |
| ML | Machine Learning |
| OEM | Original Equipment Manufacturer |
| ODD | Operational Design Domain |
| OTA | Over-The-Air |
| OVIN | Ontario Vehicle Innovation Network |
| QEW | Queen Elizabeth Way |

| | |
|---|---|
| R&D | Research and Development |
| RDII | Regional Defence Investment Initiative |
| RTDS | Regional Technology Development Sites |
| RUL | Remaining Useful Life |
| SOH | State-of-Health |
| SME | Small and Medium-sized Enterprise |
| TRL | Technology Readiness Levels |
| TTC | Toronto Transit Commission |
| V2X | Vehicle-to-everything |

# 7. OVIN Team

Information on OVIN team members and relevant contacts for outreach is available on OVIN's website at: https://www.ovinhub.ca/connect/team/

# 8. Disclaimers

This report was commissioned by the Ontario Centre of Innovation (OCI) through a Request for Proposals titled "Ontario Vehicle Innovation Network (OVIN) – Annual Comprehensive Sector Report & Quarterly Specialized Reports," dated September 26, 2025, and has been prepared by MNP LLP. It is one of five reports covering an analysis of Ontario's automotive technology, electric vehicle and smart mobility landscape while incorporating implications for the sector's skills and talent landscape.

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# 9. Expert Interviews

The project team conducted targeted consultations with industry, public sector, technology developers, regulators, and academia between April 2026 and May 2026. Consistent with the engagement protocol, interviews were non-attributable and findings are presented in aggregated form. The table below summarizes the organizations and areas of expertise represented in these consultations.

| Organization | Interviewees |
|---|---|
| Clockwork Energy | Andrea Curry, CEO |
| Gatik | Richard Steiner, Vice President of Government Relations and Public Affairs |
| Ministry of Transportation Ontario | Michael DeRuyter, Acting Director of the Cabinet, Regulatory, Intergovernmental and Strategic Policy Branch |
| Nuport | Raghavender Sahdev, CEO |
| Raven Connected | Daniel Crawford, Director of Research and Development |
| University of Waterloo | William Melek, Professor, Department of Mechanical and Mechatronics Engineering |
| University of Toronto | Steven Waslander, Professor, Institute for Aerospace Studies |
| Schaeffler Canada Inc. | Anand Gandhi, Advanced Innovation Lead of the North American region<br>Prashant Reddy, Regional head for Engineering, Digitalization and IT |

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