ARTIFICIAL INTELLIGENCE FOR CLIMATE CHANGE MITIGATION ROADMAP (SECOND EDITION)

CHAPTER 6:

ROAD TRANSPORT

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Road transport is a critical part of the global economy. Current modes of road transport rely heavily on fossil fuels, producing roughly 18% of global energy-related carbon dioxide (CO_2) emissions.[1,2] Strategies for reducing CO_2 emissions from road transport include deploying electric vehicles (EVs), using alternative fuels, adopting intelligent transportation systems (ITSs), shifting to shared modes of transport and deploying autonomous vehicles (AVs).

Plug-in electric vehicle

Vehicle electrification is the dominant strategy for reducing CO_2 emissions from road transport. Life-cycle greenhouse gas (GHG) emissions from EVs are already significantly lower than those from comparable vehicles with internal combustion engines. (Emission benefits vary based on regional differences in energy generation. One recent study found EV life-cycle emissions were lower by 66–69% in Europe, 60–68% in the United States, 37–45% in China and 19–34% in India.[3]) As electric grids decarbonize and EVs become more efficient in terms of distance per kWh and manufacturing materials employed, EVs will contribute even more to reducing emissions. Barriers to accelerated deployment of EVs include their up-front purchase price and driving range, both of which can be addressed with battery and electric motor innovations.

Other important strategies for reducing CO_2 emissions from road transport include:

- Alternative fuels. The energy properties of biofuels, synthetic fuels, hydrogen and natural gas make them attractive options for many kinds of transport, including heavy duty vehicles carrying large loads over long distances.
- Intelligent transportation systems (ITSs). Sensor and communication technologies combined with data processing can analyze vast amounts of real-time data to plan, monitor and control transit and congestion.
- Modal shifts. Shifts from personal vehicles to shared vehicles and/or public transport are also important for changing the transportation landscape.
- Autonomous vehicles (AVs). AVs have the potential to reduce CO_2 emissions by accelerating EV adoption and facilitating platooning, among other changes, but could also increase CO_2 emissions by making it easier to use individual vehicles, leading to longer trips and displacing walking, cycling and mass transit.

Artificial intelligence (AI) has significant potential to help reduce GHG emissions in all these areas. Many solutions are still in research and pilot stages but show great promise. To realize AI's immense potential to reduce road transport emissions, AI solutions must be built into commercial products, integrated into public infrastructure and deployed in a safe and responsible manner.

In this chapter we discuss how emerging capabilities of AI are opening up new opportunities to reduce CO_2 emissions from road transport.[4]

A. Vehicle Electrification

AI has the potential to play a major role in reducing carbon emissions by improving battery and electric motor design, optimizing battery usage and promoting battery recycling.

i. Material discovery

One especially promising example is AI's ability to help improve battery and electric motor design by speeding the process of material discovery. Discovering new materials is a complex task comprising two core challenges.[5] The first challenge involves determining the right chemical components that, in combination, exhibit certain desired characteristics and properties. The second challenge involves finding a structure that provides a stable solution. The key to this process often lies in reducing the very large number of possible solutions to a small number that can be evaluated in real-world experiments in a more cost- and time-effective manner.[6] AI can increase accuracy when predicting the properties of materials and accelerate down-selection of possible solutions.[7]

Indeed this is already happening. Google has discovered 2.2 million new crystals—including 380,000 stable materials—via Graph Networks for Materials Exploration (GNoME). Google researchers estimate this discovery is equivalent to nearly 800 years' worth of non AI-based research, dramatically increasing the speed and efficiency of discovery by predicting the stability of new materials.[8] Major AI-driven breakthroughs and innovations in battery materials—including in nickel cathodes, silicon anodes and novel electrolytes—are already increasing capacity and reducing the cost of EV batteries.[9]

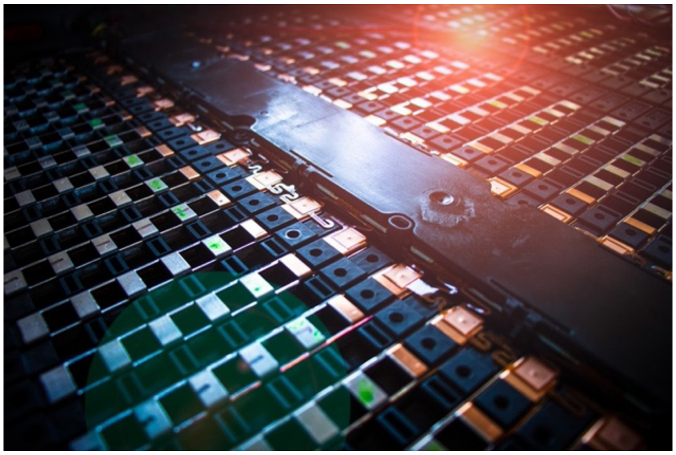
More progress could be achieved through AI investments that support collaborations between industry and academia based on data, model and knowledge sharing. Such work is underway at the US Joint Center for Energy Storage Research and the European Battery 2030+ Initiative.[10]

Similar materials research is being applied to electric motors. A United Kingdom company recently developed a rare-earth-free permanent magnet by identifying, synthesizing and testing more than 100 million compositions of rare-earth-free permanent magnet candidates within 3 months, a 200x increase over traditional methods. The process addresses industry challenges, such as supply chain security, cost, performance and environmental issues, and the resulting material reduces material costs by 80% and carbon emissions by 30% compared to current commercial rare-earth permanent magnets.[11]

ii. Battery efficiency and lifespan

AI can significantly enhance battery efficiency and lifespan. With data on energy prices, grid load, driving patterns, battery health and other factors, AI methods can optimize charging schedules for EVs with reinforcement learning.[12] AI-assisted battery charging can cut electricity costs, prevent overburdening the power grid, prolong battery lifespans and increase vehicle availability, particularly for EV fleet providers.[13] AI tools can also optimize the charging process directly while considering battery-aging effects and environmental conditions (such as temperature) that prevent chemical aging. Examples include (1) replacing rule-based charging strategies with Bayesian optimization combined with a linear-regression prediction model to define an extreme fast-charging protocol that maximizes battery cycle-life and reduces the traditional experimental-based approach from 500 to 16 days and (2) employing adaptive multistage constant current/constant voltage charging strategies based on a particle swarm optimization approach.[14]

AI-based battery monitoring provides various innovative methodologies to enhance battery efficiency and lifespan. Examples include: AI-empowered digital twin technology to create a digital replica of the battery system for real-time monitoring and predictive analysis. The digital twin works alongside the battery management system, using AI algorithms like long short-term memory (LSTM) for precise state-of-charge predictions and time-series generative adversarial networks (TS-GAN) for generating synthetic data. This integration enhances the monitoring process, predicts battery behavior accurately, and improves overall battery performance and safety.[15] Additionally, research into driving behavior–guided battery health monitoring focuses on the importance of incorporating real-world driving behaviors into battery health monitoring. By evaluating various health indicators and their acquisition probability under actual driving conditions, the state of battery health can be predicted with high accuracy. This approach balances performance and practicality, ensuring accurate and applicable battery health assessments in real-world scenarios.[16]



Automotive batteries

iii. Battery recycling and reuse

Another way to decrease the carbon footprint of EV batteries is to improve recycling and reuse.[17] AI can improve processes based on pyrometallurgical, hydrometallurgical and biological recycling to recover precious raw materials, while supporting diagnostics to evaluate the fit and expected characteristics for a second life. Examples of these applications are (1) useful-life forecasting,[18] (2) machine learning (ML)-enhanced automated disassembly and quality control that integrates computer vision and time- series prediction,[19] (3) optimal parameter setting for bioleaching processes for material recovery based on a random forest regression model[20] and (4) applications for battery life-cycle, waste recycling and material recovery.[21]

iv. Bidirectional charging

AI can play an important role in bidirectional EV charging.[22] With bidirectional charging capabilities, EVs can deliver power to homes (V2H), businesses (V2B) or the electric grid (V2G). Together, these applications are sometimes referred to as V2X or "vehicle-to-everything". V2X technologies provide homeowners and businesses with energy security and help grid managers overcome shortages or deliver ancillary grid services. Reinforcement learning algorithms based on user preference and price signals are a potent tool for guiding the charging and discharging in V2X systems.[23] AI can also be used in charge-management systems to guide EVs to charging stations to reduce negative effects during peak charging times.[24] The mobile storage can also be used to improve energy performance of public buildings by using an AI-based V2G strategy to reduce the carbon footprint of buildings supported by energy consumption and cost predictions.[25]

To realize AI's full potential to contribute to vehicle electrification, interoperability of AI systems will be important. Defining protocols for interoperability of AI systems across different EV models and charging infrastructures can help ensure seamless integration and operational efficiency.

EV fleet charging

B. Alternative Fuels

Alternative fuels can play an important role in reducing CO_2 emissions from road transport. Synthetic fuels and biofuels provide transitional solutions that can leverage existing infrastructure and reduce emissions in the near term. Compressed natural gas (CNG) and liquefied natural gas (LNG) serve as lower-emission alternatives to conventional fuels, particularly in regions with abundant natural gas resources. The optimal mix of these technologies will depend on regional resources, infrastructure and specific transportation needs. Each technology has its own strengths and challenges, and their importance varies by application and context. These alternative fuels also have applications beyond road transport, including in air and marine travel.

Biofuels can help decarbonize road transport. The most promising applications are with heavy duty vehicles, such as trucks carrying large loads over long distances. Although caution is required. When feedstocks other than waste biomass are used for biofuels, indirect effects of land use change can reduce or even eliminate the GHG benefits of using biofuels. AI can play an important role in developing sustainable biofuels. Applications include image segmentation for cell analysis in microalgae and modeling time series in the bioenergy conversion process. For new biofuels, AI already plays an important role in predicting and optimizing highly complex non-linear bioenergy systems. When it comes to producing biofuels from biomass, so far most of the literature involving AI focuses on thermochemical processes,[26] however biological processes offer a promising research direction.[27] AI models can also help evaluate biofuel infrastructure requirements and support policy making and long-term planning.[28]

Synthetic Fuels, also known as synfuels, are produced through chemical processes, such as Fischer-Tropsch synthesis, which converts carbon monoxide and hydrogen into liquid hydrocarbons suitable for vehicle engines.[29] Audi's "e-diesel" is an example of a synthetic diesel fuel produced using renewable energy, suitable for standard diesel engines without modifications. The production process involves electrolysis to separate hydrogen from water molecules, combined with CO_2 to create liquid hydrocarbons. AI enhances the efficiency of Fischer-Tropsch synthesis by optimizing reaction conditions and developing more effective catalysts.[30] AI-driven process simulations help identify and mitigate inefficiencies, reducing the carbon footprint of synthetic fuel production and usage in road transport.

Hydrogen Fuel Cells generate electricity by combining hydrogen gas stored in high-pressure tanks with oxygen, producing only water vapor as an emission. The Toyota Mirai is a hydrogen fuel cell vehicle (FCV) that uses this technology, offering a driving range comparable to gasoline vehicles with refueling times of about five minutes. AI optimizes fuel cell design and the hydrogen production process, particularly electrolysis, by predicting the performance of materials and operational parameters.[31] Predictive maintenance and integration with renewable energy sources are enhanced by AI, reducing the carbon footprint of hydrogen production and fuel cell operation.

Compressed Natural Gas (CNG) is a cleaner-burning alternative to gasoline, producing fewer emissions and often used in fleets for companies or municipal services. The Honda Civic Natural Gas vehicle is an example, featuring a modified engine and fuel system to accommodate CNG. AI improves CNG technology by optimizing combustion processes, analyzing real-time engine data, and enhancing natural gas extraction and processing.[32] AI-driven analytics also help design efficient storage and distribution systems, reducing the carbon emissions associated with CNG production, distribution and consumption in road transport.

Liquefied Natural Gas (LNG) is used in heavy-duty trucks for long-haul trucking due to its higher energy density compared to CNG. The Freightliner Cascadia is a heavy-duty truck equipped with an LNG fuel system, providing a cleaner alternative to diesel-powered trucks. AI optimizes the LNG liquefaction process, improves plant performance and enhances routing and scheduling of LNG shipments. Predictive maintenance extends the lifespan of LNG infrastructure, while AI-driven improvements in the regasification process reduce energy input and emissions, making the LNG supply chain more sustainable and environmentally friendly.[33]

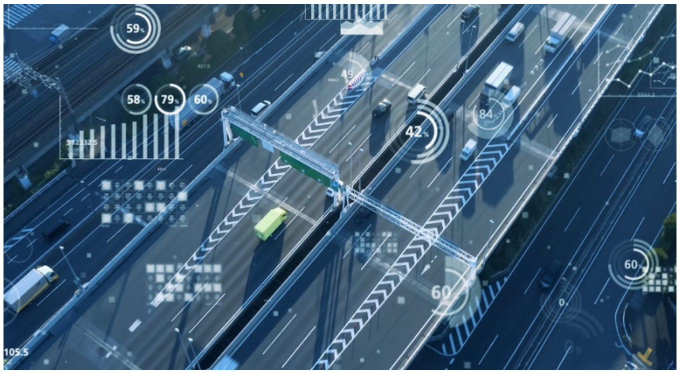
C. Intelligent Transportation Systems (ITSs)

AI, sensors and communications networks can be used in combination to manage transportation infrastructure. An ITS with these components can help plan transportation infrastructure, coordinate traffic, manage EV charging networks and predict maintenance needs. ITSs can adjust digital signs, traffic signals and public transportation schedules to react to forecasted congestion. They can schedule maintenance to avoid material failure and increase road safety. ITSs have great potential to help reduce congestion, optimize vehicle and infrastructure usage, and improve safety while reducing emissions from road transport.[34] These technologies could be at the heart of a more sustainable and carbon-free transportation system.

i. Traffic management

AI can help optimize traffic flow, decrease congestion, enable dynamic traffic-light sequencing, suggest smart multi-modal public/private routes and model traffic to foresee and alleviate congestion. These AI strategies have substantial potential sustainability benefits, including reduced fuel consumption and GHG emissions, which in turn enhance urban air quality and support environmental sustainability goals.

Some cities have implemented pilot studies to investigate real-world implications of using AI for traffic management. The city of Phoenix in the United States saw a 40% decrease in vehicle delay time after implementing an AI-driven traffic management system. In Calabria, Italy, a pilot program reduced total travel time by up to 55% through adaptive real-time control of traffic signals for connected vehicles (CV).[35] Case studies have shown that AI-driven traffic management systems can reduce traffic congestion by up to 30% during peak times and 15–20% overall by providing 45- to 60-minute congestion-prediction lead times.[36]



Vehicles connected by intelligent transportation system

AI can predict traffic congestion through advanced analytics by leveraging historical and real-time data from various sources, such as sensors, GPS devices and traffic cameras. Techniques based on deep learning enable AI systems to learn intricate traffic patterns and accurately forecast congestion and traffic anomalies. Real-time data integration allows these systems to provide timely insights, enhancing their predictive accuracy.[37] AI also plays a critical role in incident detection and response, where AI-powered surveillance systems can identify accidents or road hazards in real-time, allowing for immediate alerts to authorities and rapid response to minimize traffic disruptions. Dynamic routing optimization further helps alleviate congestion by using reinforcement learning algorithms, such as Q-learning, to adjust vehicle routes in real-time, thereby optimizing traffic flow and reducing travel times. AI-driven traffic signal coordination, exemplified by initiatives like Google’s Project Green Light,[38] enhances traffic efficiency by optimizing signal timings based on current conditions.

In public transport, AI can be used to predict passenger loads and optimize schedules and routes, enhancing service efficiency and user satisfaction.[39] AI’s role in predictive maintenance can also help foresee potential infrastructure issues in public transit, preventing failures or delays. In addition, AI traffic congestion prediction can be used to schedule increases in public transport capacity. Finally, by processing and analyzing ITS data, AI will be able to aid informed policy decisions and strategic planning, leading to greener, more efficient public transit systems. Infusion of AI into ITSs is emerging as a cornerstone strategy in shifting toward lower emissions and heightened efficiency in public transit.

ii. Data needs

The data needed for successful AI applications can be provided by static or mobile sensors. Sensor-driven infrastructure components—collecting and transmitting data—are essential.[40] These include traffic sensors at intersections or along roadways, smart traffic lights with sensors to monitor traffic and pedestrian activity, road weather information systems that track atmospheric and pavement conditions, and smart parking sensors that detect vehicle presence. Sensors on bridges, tunnels and roads to facilitate predictive maintenance, as well as environmental sensors to monitor conditions like air quality and emissions, are also important. In the realm of CVs, sensor-driven infrastructure can dynamically integrate vehicle sensors—such as LiDAR, radar and cameras—in ITSs to perceive the surrounding environment through edge (distributed) analytics.[41] By offering continuous, real-time data, a sensor-driven infrastructure enables AI systems to significantly enhance operational capabilities of infrastructure, helping route emergency services, control traffic and respond to demand changes in public transport. However, the massive amounts of data require smart integration with cloud-based storage and potentially large computing capabilities that may have a negative impact on net emissions.[42]

Digital connectivity and emerging technologies, such as vehicle-to-vehicle (V2V) and vehicle-to-infrastructure (V2I) communications, are cornerstones of Cooperative Intelligent Transport Systems (C-ITS). Such systems enable coordinated exchange of data for real-time analytics and collection of data to train the next generation of intelligent systems.[43] New sensors for C-ITS have been shown to increase resilience for transportation systems, with immediate impact on operation and infrastructure robustness.[44] However, interconnectedness between individual vehicles, roadside units and central data processing may increase the risk of data exploitation and invasions of privacy, warranting new methods for privacy protection in these systems through emerging technologies, such as blockchain[45] and federated learning.[46]

iii. Simulations

AI-driven simulation has significant potential to reduce road transport emissions, delivering better results than conventional algorithm-based simulations by capturing complex patterns and relationships in transportation data.[47] This can provide a wealth of insights, including in optimizing infrastructure planning, forecasting energy demand and evaluating potential transportation system policies.[48] AI simulations can help identify where investments in charging stations and bicycle lanes can best reduce emissions, for example. Linking transportation and energy systems in AI-driven simulations can significantly advance the evolution of ITSs, contributing to more sustainable and efficient transport networks. A 2021 Latvian study, for example, showed the potential of different policy instruments to reduce CO_2 emissions 30% by 2030, concluding that more research and a tighter coupling between the transportation and energy sectors are needed to reach the ambitious goals of the European Green Deal.[49]

As simulations become more powerful, more data are needed, and real-world experiences can provide the best insights. Communities, utility providers, fleet operators and vehicle manufacturers could initiate more pilot projects, such as dynamic traffic light control systems, which leverage real-time data from GPS, traffic flow sensors, transportation network health and weather updates to optimize the sequence and timing of traffic lights using ML methods. These pilot projects can enhance traffic flow, reduce congestion and curtail fuel consumption. However, securing a large enough number of participants will be key to gaining meaningful insights. Other initiatives could involve predictive maintenance of road infrastructure using sensors that monitor wear and tear, schedule preemptive maintenance and mitigate critical failures.[50] Such collaborative, large-scale projects not only improve transportation efficiency, safety and user experience, but also contribute significantly to reducing carbon emissions.

iv. Foundation models

As a final consideration, the advent of foundation models, prompted by recent advances in large-language and vision models, has marked a significant shift in our approach to problem-solving. These models, with their capacity to handle multi-modal input and domain-specific expertise, have the potential to revolutionize numerous fields. However, their applicability in the realm of road transport is relatively uncharted. Potential applications for foundation models may include autonomous driving and control of intelligent transportation infrastructure, however their impact is not yet clear.[43]

D. Modal Shifts

Modal shifts—moving from one type of transportation to another—can significantly reduce emissions from road transport. Leading examples include shifts from private vehicles to public transit and from solo driving to car sharing. Such modal shifts require behavior changes and often depend on transit systems that offer an array of mobility options.

AI can serve as a powerful tool in driving behavioral change that contributes to sustainable mobility. AI-driven approaches encourage the use of public transportation in several ways:

- First, by harnessing AI algorithms to analyze various data sources, AI-driven approaches can predict public transit demand, allowing for optimal route planning and strategic relocation that enhances the convenience of public transit.
- Second, by underpinning integrated mobility platforms, which process real-time information from multiple transport modes and propose optimal route options, AI platforms can nudge users toward public or shared transport. In addition, AI-guided autonomous public transit could extend the reach of public transport to regions where traditional services may not be economically viable, thus decreasing reliance on private vehicles.
- Third, by producing personalized recommendations and effective gamification techniques, such as reward systems, challenges or social competitions, AI-driven approaches can incentivize and engage commuters in choosing sustainable transportation options.
- Finally, by predicting maintenance issues in public transportation vehicles, AI-driven approaches can improve the dependability of these services by minimizing downtime. Consequently, AI can make public transportation more efficient, reliable and appealing, playing a crucial role in curtailing private vehicle usage and overall transport activity.

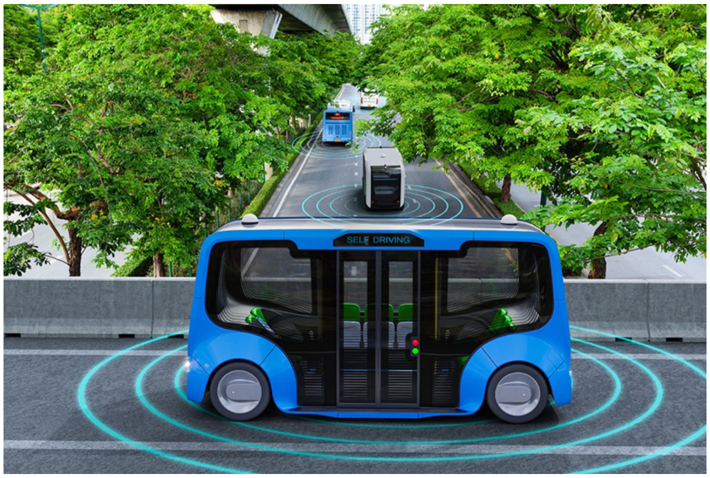
AI can also enable shared mobility solutions, which can significantly cut down on energy consumption and GHG emissions.[51]

- AI can help manage shared vehicle fleets, ensuring that vehicles are distributed effectively based on anticipated demand, reducing waiting times, and making shared mobility more effective and attractive.[52]
- AI can also personalize the shared mobility experience by understanding users, suggesting the most suitable shared options and facilitating dynamic pricing with prices based on supply and demand to balance resource utilization and maintain service attractiveness.[53]
- AI-driven predictive maintenance can keep shared vehicles in optimal condition, maintaining energy efficiency, reducing downtime and enhancing reliability of shared mobility services.[53]

Thus, through these measures, AI can make shared mobility a more appealing alternative to private vehicle use, leading to a significant reduction in overall transport activity.

E. Autonomous Vehicles (AVs)

One of the most important emerging uses of AI in the road transport sector to date is with AVs.[54] AVs have made significant progress in real-world deployments, with companies like Waymo and Cruise operating commercial robo taxi services in select US cities, while autonomous trucking firms, such as TuSimple and Kodiak Robotics, have conducted extensive on-road testing.[55] As of 2023, AVs had driven over 80 million miles on US public roads, demonstrating the scale of ongoing testing and development efforts.[56] However, widespread deployment remains limited, with most autonomous vehicle operations restricted to specific geographic areas and operating conditions.[57]



Autonomous shuttle bus

AVs and more specifically autonomous electric vehicles (AEVs) have the potential to reduce CO_2 emissions by reducing dependence on conventional, individual-owned internal combustion engine vehicles and promoting shared electric and autonomous transport. AI can be used to enhance accessibility and convenience, as route optimization and vehicle distribution make AEVs that are integrated into shared mobility platforms highly reliable and accessible. Furthermore, AEVs can lower operating costs due to their electric drivetrains, a benefit that AI can augment by optimizing energy usage. AI also enables AEVs to operate more efficiently, through measures such as platooning, smart parking management and route selection. This efficiency reduces congestion, energy use and urban space requirements. Additionally, the environmental impact is minimized as AEVs produce no tailpipe emissions and AI aids in optimizing energy usage. Lastly, AI can facilitate integration of AEVs with public transit, enhancing first-mile and last-mile connectivity, making public transit a more appealing choice and further driving the modal shift.

Studies show that AVs are expected to bring noticeable changes to road transport and, through them, reduce environmental impacts and CO_2 emissions.[58] However, AVs could also increase emissions of CO_2.

- Cheap, convenient on-demand mobility may overshadow alternatives, such as walking, cycling and public transport. Drivers may be more prone to take longer trips when driving requires little attention. The result could be more vehicle kilometers traveled and greater emissions.[59]
- In addition, rebound effects can occur when savings from efficiency improvements lead to increased demand for a product, reducing or even negating the original savings.[60]
- As AVs and smart infrastructure are algorithm-driven, malfunctions could result in significant inefficiencies, unexpected behaviors or accidents that require corrective actions, potentially leading to additional carbon emissions.

F. Barriers

While AI has immense potential to help reduce GHG emissions from road transport, several barriers must be addressed to realize this potential.

A first barrier is lack of data. Data on a wide range of topics are required to deploy AI in integrated road transportation systems. Sensors, smart infrastructure and other tools will be needed to collect such data. While algorithm development and improved computing hardware are important, near- to mid-term advances primarily depend on availability and accessibility of data.

Second, uniform standards and protocols for sensor data collection and communication are essential. In a modern grid, a vehicle can serve as a communication node and operate as a channel to interconnect the electricity grid, traffic network and communication network.[61] In this context, developing common standards in V2V and V2I communication is important for promoting seamless interoperability. A standardized communication framework enables vehicles to exchange information effectively with their environment. This capability provides additional data that can inform local predictions and decision making, reducing emissions while increasing the efficiency and safety of the transportation system.

A third barrier is a shortage of personnel with the needed training in and familiarity with AI. AI experts and software developers are needed, but—at least as important—transport operators and regulators must be equipped with the necessary skills to consider and evaluate AI options.

G. Risks

Using AI in road transport also creates risks that must be addressed.

First, privacy interests can be threatened by the extensive data collection needed for many applications. Those data could potentially reveal a great deal about individuals' habits and actions.

Societal norms are only beginning to be established with respect to collecting, distributing and using data in this area.

Second, using AI in road transport creates risks of bias. For example, training data sets may sample more heavily from wealthy neighborhoods than poor ones. Inadvertent discrimination against certain groups or areas is possible. Close attention is required to minimize the risk of inadvertent bias emerging from use of AI.

A third and serious risk is higher emissions as a result of deploying AVs, as noted above. AVs might lead to far more driving, increasing emissions from driving and vehicle manufacturing.[62]

Predicting the impact of AVs on road transport emissions is challenging due to several factors, including ongoing technological development, market evolution and regulatory actions. To address potential negative impacts, a holistic and sustainable approach to integrating AI in the transportation sector is crucial. Careful planning will be necessary to prevent unintended consequences and manage potential increases in vehicle usage.

H. Recommendations

Vehicle Electrification

1. *Local governments should promote development and deployment of AI-optimized EV charging stations, update building codes that require incorporating such systems in new installations, and run public awareness campaigns to educate residents and businesses about the benefits of intelligent EV infrastructure.*

2. *Industry and academia should form partnerships to drive innovation in AI-enhanced EV technologies. These collaborations should focus on developing AI-driven solutions to improve battery lifespan, efficiency and recycling methods.*

3. *National governments, industry and academia should invest in AI research for battery and motor advancements, leveraging HPC for materials discovery; integrating AI methods to enhance performance, safety and lifespan; and promoting collaborations such as the US Joint Center for Energy Storage Research and the European Battery 2030+ Initiative.*

4. *National governments should establish comprehensive regulations for AI applications in EV technology on topics including data privacy, usage and storage. These regulations should align with global standards to facilitate international cooperation and ensure responsible and ethical use of AI tools.*

5. *Industry and standards development organizations should work together to develop standards for AI applications in EVs, covering topics such as battery monitoring, charging optimization and communication protocols.*

Alternative Fuels

1. *National governments should implement incentive programs such as subsidies and grants, to encourage AI-driven research and development of alternative fuels. They should also increase simulation capabilities to evaluate the life-cycle and infrastructure impact of innovative fuels.*

2. *Industry and academia should increase collaborative research efforts to enhance efficiency and reduce the environmental impact of alternative fuels based on AI methods, for example by establishing innovation hubs and providing funding and support for startups working on AI-driven technologies in these fields.*

3. *Governments, academia and industry should develop centralized data-sharing platforms where researchers can access and share datasets related to alternative fuels to facilitate data exchange, enhance research quality and speed up discoveries.*

Intelligent Transportation Systems (ITSs)

1. *National governments and intergovernmental organizations should establish comprehensive data privacy regulations for AI applications in transportation following examples such as the United Nations' global AI resolution. These regulations should ensure clear guidelines to safeguard human rights, protect personal data and support AI use to mitigate climate impact in road transport.*
2. *Local governments should invest in smart infrastructure and develop long-term strategic plans, implementing procurement policies, conducting public awareness campaigns and investing in sensor-driven infrastructure for AI-based real-time decision making.*
3. *Industry and standards development organizations should collaborate to establish standards for smart transportation technologies, including V2X communication, data security, EV charging connectors and harmonized communication networks leveraging 5G and satellite technology to ensure integration and distributed interoperability.*
4. *National governments, industry, and academia should increase research and data collection for intelligent transportation systems to support AI in mitigating climate impact in road transport, enabling complex simulations using HPC, and launching large-scale collaborations and pilot projects for smart infrastructure development.*

Modal Shift

1. *National governments should allocate funding for AI projects that optimize multi-modal transit routes, predict demand and improve shared mobility services, ensuring a streamlined and transparent application process for research institutions and private companies to access these funds.*
2. *Governments, industry, and academia should form consortia to develop AI-driven mobility platforms in major cities, integrate pilot projects to test strategies like dynamic pricing and optimized public transit schedules, and publish findings for wider implementation.*

Autonomous Vehicles (AVs)

1. *Local and national governments should collect and share data on the GHG impacts of AVs, including data on supply chain emissions.*
2. *Local governments should develop regulations and run pilot projects to facilitate integration of AI-driven autonomous mobility solutions that reduce CO_2 emissions.*
3. *Industry and academia should expand research efforts and develop improved simulation capacities to help develop AI-based methods that offer a safe test bed for evolving autonomous driving capabilities, focusing in particular on ensuring that AVs help reduce CO_2 emissions.*

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