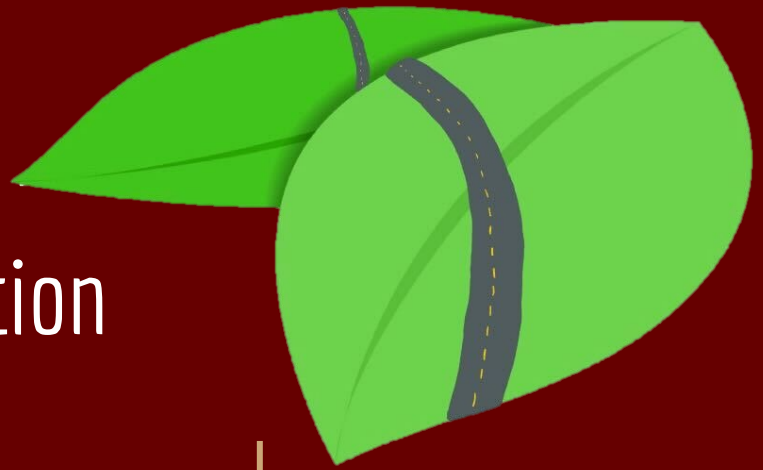
AI in Transportation



Cathy Wu

Associate Professor | MIT LIDS, CEE, & IDSS

Pre-readings

- **Climate change sector overview for transportation**
  - Jaramillo, Paulina, et al. *Climate Change 2022: Mitigation of Climate Change. Contribution of Working Group III to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change* (**Chapter 10: Transport**). IPCC, 2023. (IPCC Executive Summary)
- **AI for transportation**
  - Transportation Research Board Executive Committee, *Transforming Transportation: Leveraging the Power of Artificial Intelligence, Digitalization, and Automation*. Washington, D.C.: National Academies Press, 2026. doi: 10.17226/29350. (PDF)
- **AI for climate change (transportation focus)**
  - Sandalow, David B. et al., *Artificial Intelligence for Climate Change Mitigation Roadmap* (**Chapter 6: Road Transport**), 2nd Ed. Academic Commons, 2024. (PDF)
  - D. Rolnick et al., "Tackling climate change with machine learning" (**Section 2: Transportation**), Jun. 2019. Available: http://arxiv.org/abs/1906.05433v2

Learning objectives

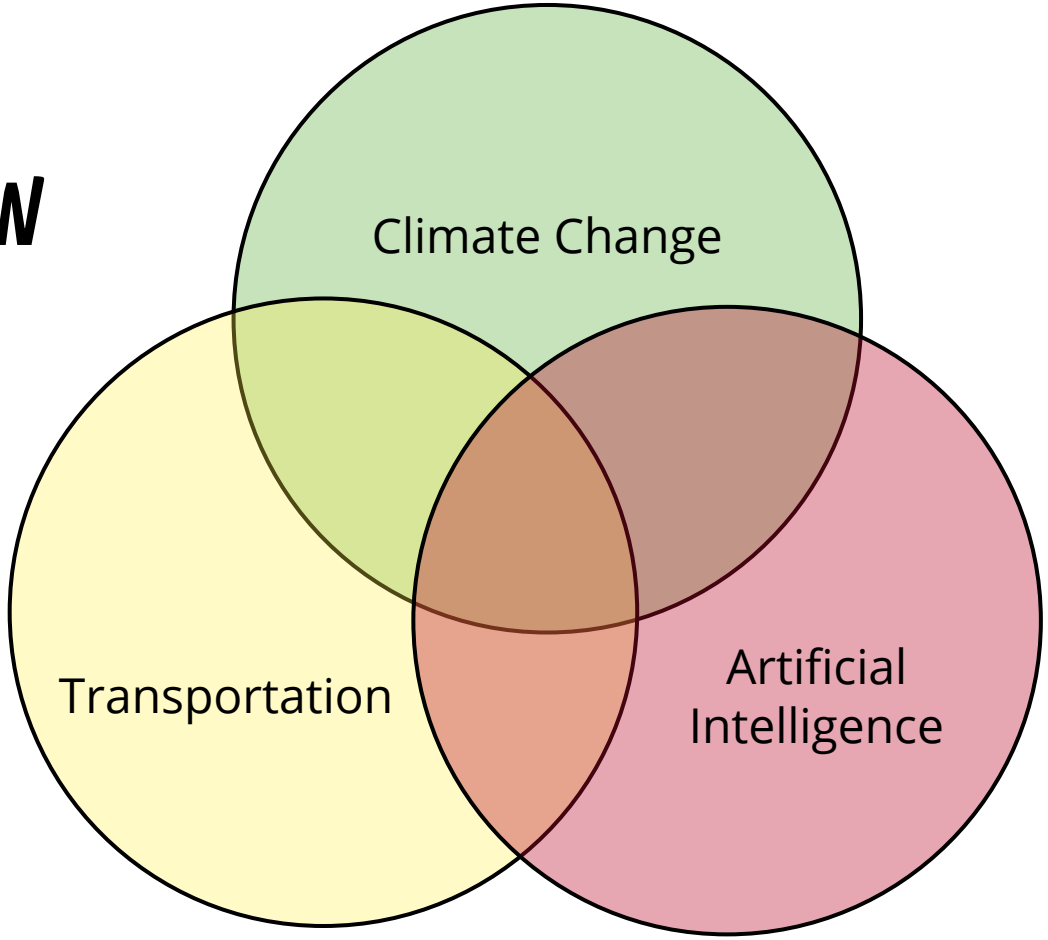
This lecture is designed around gaining insight into these questions:

- Why is transportation difficult to decarbonize?
- Which interventions are important for mitigation?
- Where can AI really help, and where is it a distraction?
- What are the ethical and equity risks of mitigation strategies?

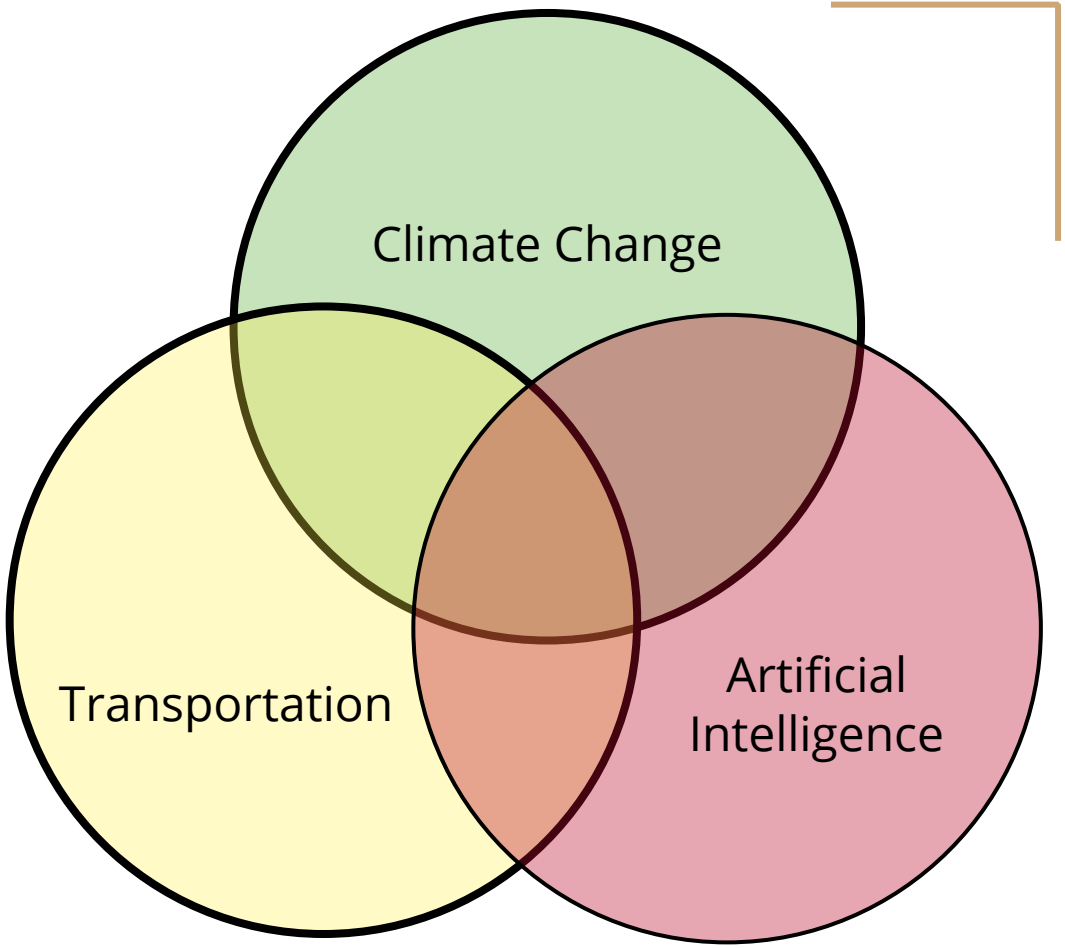
Outline

- Sector Overview
  - Transportation emissions snapshot & targets
  - Why transportation is hard to decarbonize
  - Decarbonization framework
  - AI in Transportation overview
  - AI for Climate Change Mitigation in Transportation
- Deep Dive
  - Improve: AI for Electrification
  - Shift: AI for Modal Shift
  - Improve: AI for Transport Efficiency
- Final remarks
  - Synthesis, entry points, and next steps

Sector Overview
Transportation, Climate Change, and AI



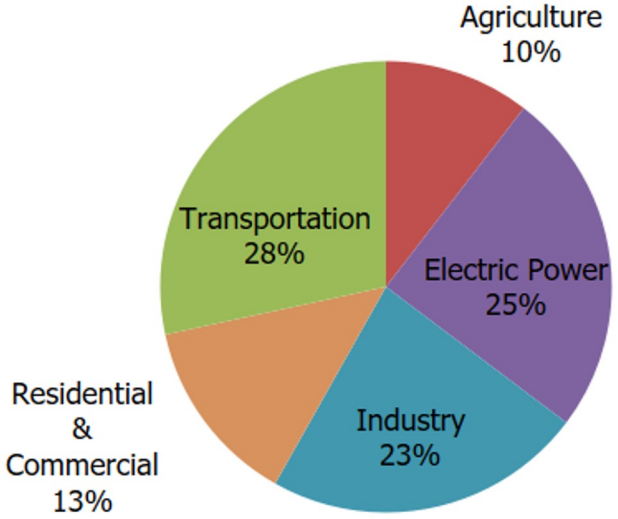
Transportation emissions snapshot & targets



United States: GHG snapshot and goals

- Paris Agreement goals [1]
  - 45% reduction from 2010 levels by 2030
  - Net zero by 2050
- United States [2]
  - National GHG peaked in 2005
  - Goal: 50-52% reduction in 2005 levels by 2030
  - 2025: GHG 18% below 2005 levels.
- Transportation is largest sector of GHG emissions in the US [3]

Total U.S. Greenhouse Gas Emissions by Economic Sector in 2022



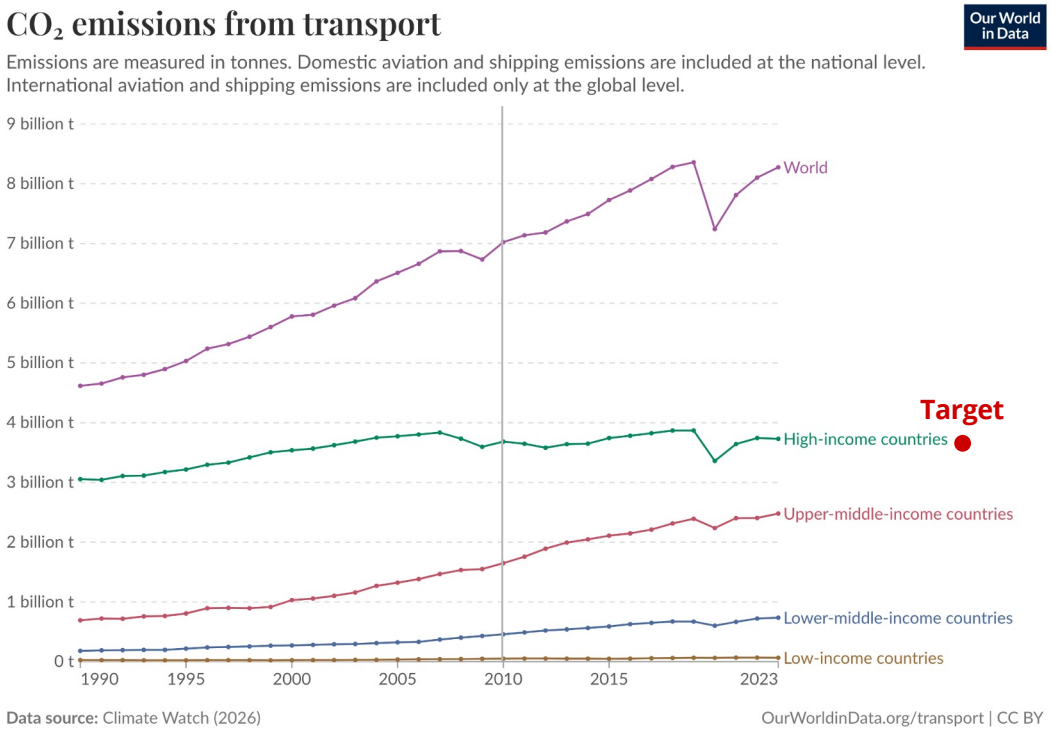
Source: Inventory of U.S. Greenhouse Gas Emissions and Sinks, US EPA, 2026.

[1] Rogelj, J., D. et al, 2018: Mitigation Pathways Compatible with 1.5°C in the Context of Sustainable Development. In: Global Warming of 1.5°C. An IPCC Special Report on the impacts of global warming of 1.5°C above pre-industrial levels and related global greenhouse gas emission pathways, in the context of strengthening the global response to the threat of climate change, sustainable development, and efforts to eradicate poverty. Cambridge University Press, Cambridge, UK and New York, NY, USA, pp. 93-174, doi:10.1017/9781009157940.004.

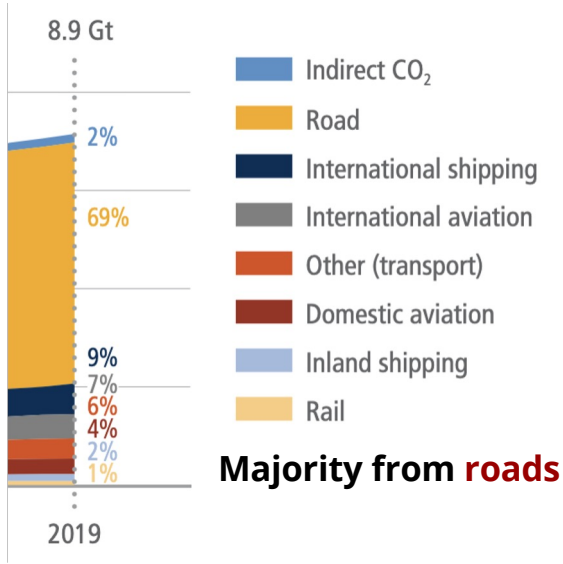
[2] U.S. Department of State. (2021). The United States of America's Nationally Determined Contribution: Reducing Greenhouse Gases in the United States: A 2030 Emissions Target. Submitted to the United Nations Framework Convention on Climate Change (UNFCCC) in 2021.

[3] "Inventory of U.S. Greenhouse Gas Emissions and Sinks." US EPA, 10 June 2026, url.

Transportation Sector Contributions to Climate Change



23% of global energy-related CO_2 emissions and increasing



Majority from roads

Jaramillo, P., et al., 2022: Transport. In IPCC, 2022: Climate Change 2022: Mitigation of Climate Change. Contribution of Working Group III to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change. Cambridge University Press. doi: 10.1017/9781009157926.012

How are we doing?

- On track
- More efforts needed
- Not on track

Tracking Transport

Not on track

In 2022, the rebound in passenger and cargo transport activity following the coronavirus (Covid-19) pandemic led to a 3% increase in transport CO_2 emissions compared to the previous year. Transport emissions grew at an annual average rate of 1.7% from 1990 to 2022, faster than any other end-use sector except for industry (which also grew at around 1.7%). To get on track with the Net Zero Emissions (NZE) by 2050 Scenario, CO_2 emissions from the transport sector must fall by more than 3% per year to 2030. Strong regulations and fiscal incentives, as well as considerable investment in infrastructure to enable low- and zero-emission vehicle operations, will be needed to achieve these emissions reductions.

- **Transport**
- **Cars and Vans**
- **Trucks and Buses**
- **Rail**
- **Aviation**
- **International Shipping**
- **Electric Vehicles**

See: 2026 report

Tracking Transport. International Energy Agency (IEA), 2023

Transportation-Adjacent Emissions (Definitions are Important)

- "Transport sector" = operational emissions
  - **Tail-pipe GHG emissions**
- Excluded: transportation-adjacent emissions, including industry sector (embodied emissions)
  - **Fuel and electricity supply**: oil extraction/refining, hydrogen production, electricity generation.
  - **Vehicle lifecycle**: manufacturing, batteries, maintenance, disposal/recycling.
  - **Infrastructure lifecycle**: roads, bridges, rail, airports, ports, concrete, asphalt, steel.
  - **Land-use effects**: sprawl, parking, induced travel, longer trip distances.
  - **Digital/automation effects**: compute, sensors, data centers, empty repositioning, induced travel.

Why Transportation is Hard to Decarbonize

Numerous mechanisms of inertia and resistance:

- **Demand continues to grow** with income, urbanization, and e-commerce;
- **Trips are spatially constrained** by land use, housing, jobs, and logistics networks
- **Assets turn over slowly** (decades): vehicles, roads, depots, ports, chargers, grids
- **Decision-making is fragmented** across households, firms, cities, utilities, and governments
- **Benefits and harms are unevenly distributed**
- **Efficiency gains can rebound** into more travel, more VMT, or longer trips (Jevons paradox)

Different transportation systems have different decision structures:

Factor	Passenger transport	Freight / heavy transport
Main bottleneck	Land use + mobility options → cost/convenience → behavior	Energy density + logistics → operating cost
Decision structure	Billions of households and travelers	Fewer firms, fleets, shippers, carriers, ports
Electrification pathway	Easier for light-duty trips	Harder for long-haul, heavy-duty cycles
Risk of induced demand	Cheaper/easier travel → more VMT	Cheaper logistics/goods → more freight activity

Decarbonization is Not the Only Goal (Multi-Objective)

Consider: Are these **competing or complementary objectives**? How well *could* they align?

Transportation goals, in no particular order:

- Decarbonization
- Access
- Affordability
- Mobility
- Safety
- Efficiency / Cost
- Public health
- Comfort / Liveability
- Air quality
- Security
- Privacy
- Resilience
- Energy security
- Local economy

Decarbonization frameworks

Lens 1: Avoid-Shift-Improve (ASI) framework

Avoid: reduce total vehicle travel

- compact land use,
- telework,
- trip chaining,
- parking reform,
- congestion pricing,
- freight consolidation.

Shift: shift travel from higher-emitting to lower-emitting modes

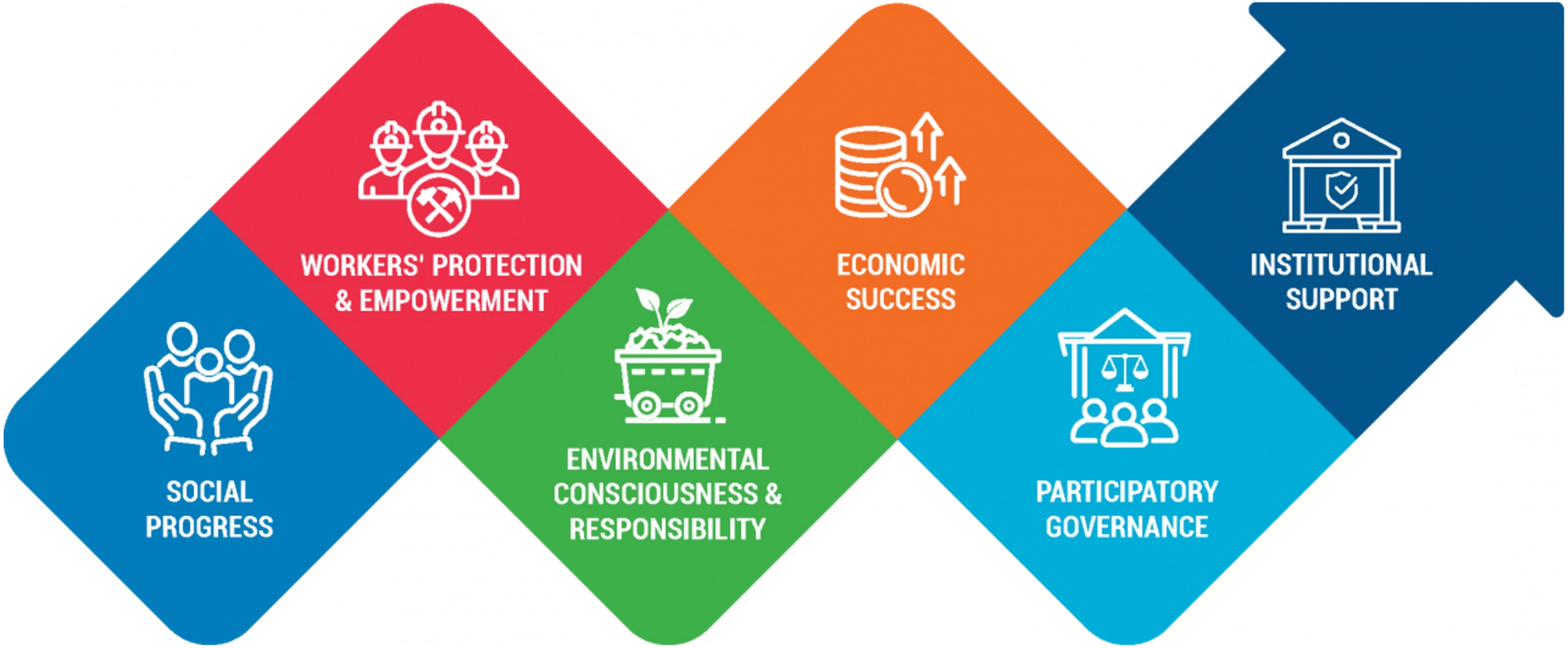
- multi-modal planning & navigation (walking, cycling, rail, public transit),
- complete streets roadway design,
- intermodal freight,
- prioritize high-occupancy vehicles,
- mobility as a service (MaaS).

Improve: reduce per-kilometre emission rates

- electrification,
- efficient vehicles,
- eco-driving & anti-idling,
- traffic operations,
- high-emitting vehicle scrappage programmes,
- lower-carbon and cleaner fuels.

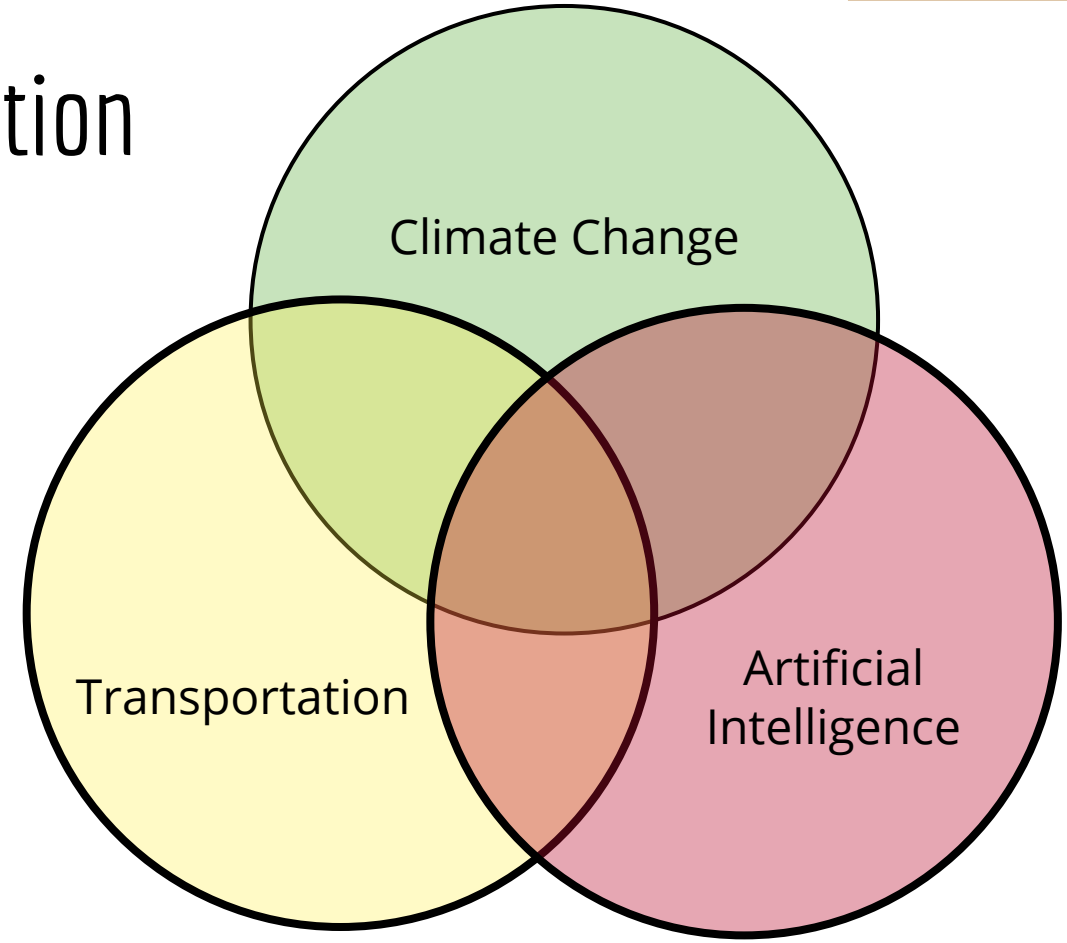
[1] P. Jaramillo and et al., “Transport,” in Climate Change 2022: Mitigation of Climate Change. Contribution of Working Group III to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change, 2024. doi: 10.1017/9781009157926.012.

Lens 2: Swift, Just and Equitable Transition

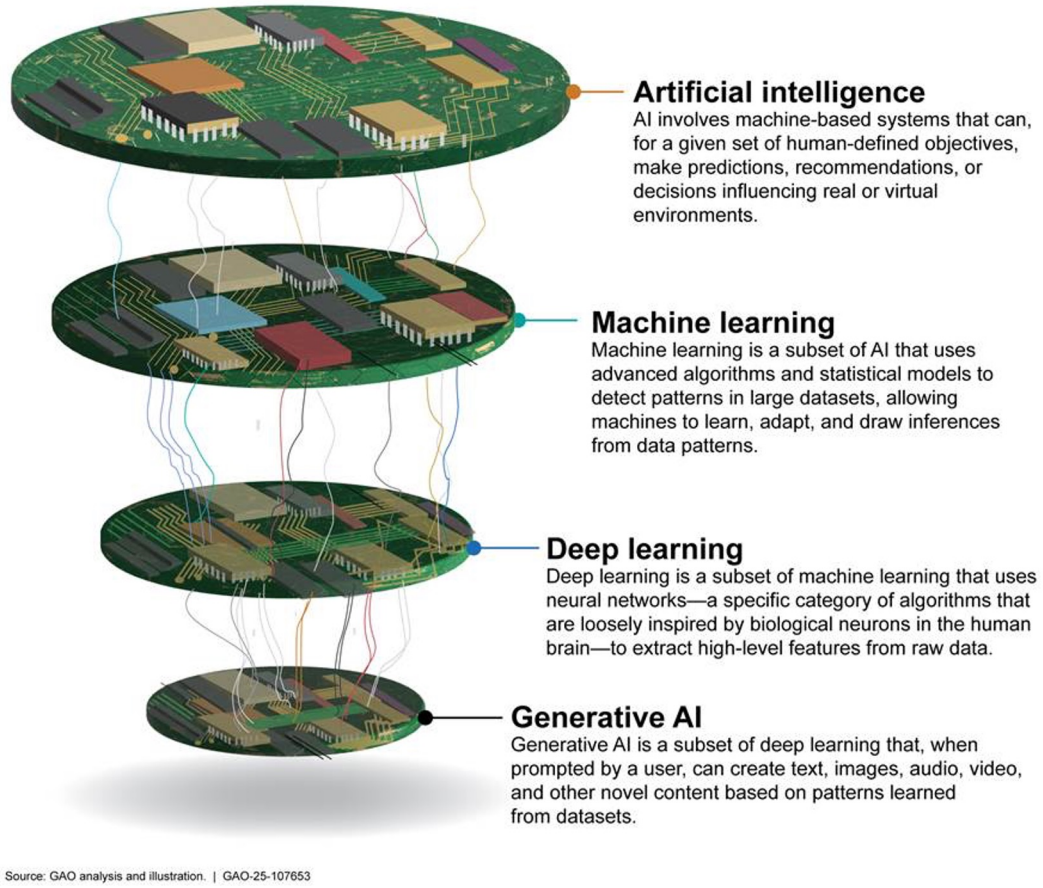


United Nations Economic Commission for Europe (UNECE), "About Just Transition," 2025, unece.org/sustainable-energy/just-transition/about-just-transition.

AI in Transportation overview



Definition of AI



[1] C. Wright and K. Walsh, “Artificial intelligence: Generative AI use and management at federal agencies,” United States Government Accountability Office, Report to Congressional Requesters GAO-25-107653, 2025. [Online]. Available: https://files.gao.gov/reports/GAO-25-107653/index.html

Common applications of AI in transport



Fig. 1. Key applications of AI, ML, and DL in advanced transportation systems.

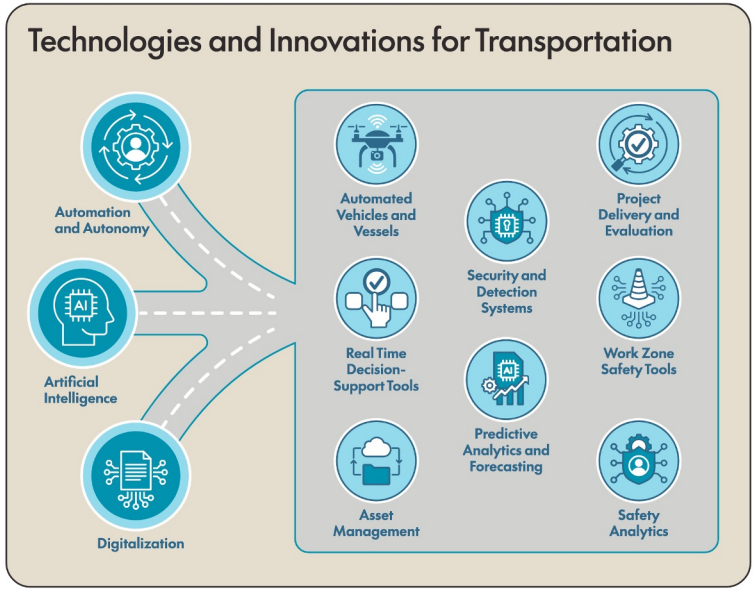


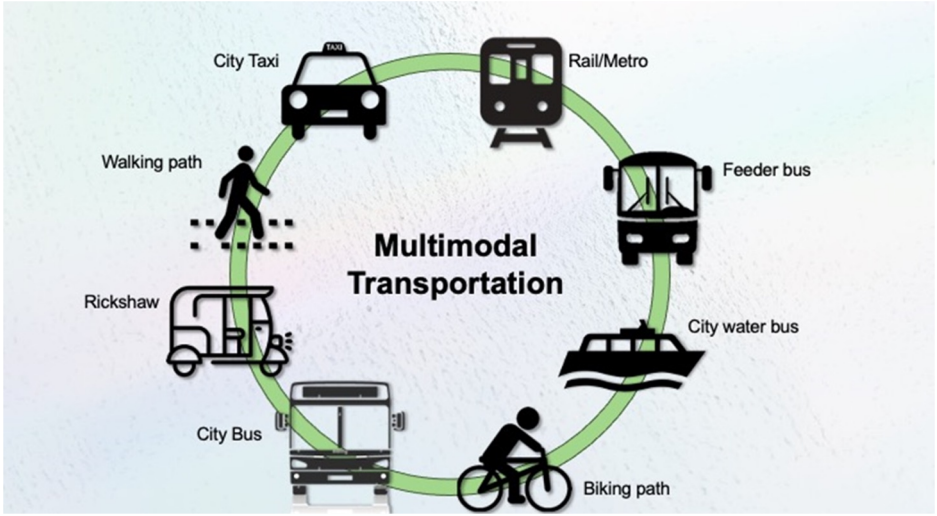
FIGURE 1. Artificial intelligence, advanced automation and autonomy, and digitalization are separately and jointly producing innovations in transportation.

[1] S. Saki and M. Soori, "Artificial intelligence, machine learning and deep learning in advanced transportation systems, a review," Multimodal Transportation, vol. 5, no. 1, p. 100242, Mar. 2026, doi: 10.1016/j.multra.2025.100242.
[2] Transportation Research Board Executive Committee, Transportation Research Board, and National Academies of Sciences, Engineering, and Medicine, Transforming Transportation: Leveraging the Power of Artificial Intelligence, Digitalization, and Automation. Washington, D.C.: National Academies Press, 2026, p. 29350. doi: 10.17226/29350.

Modes of Transportation

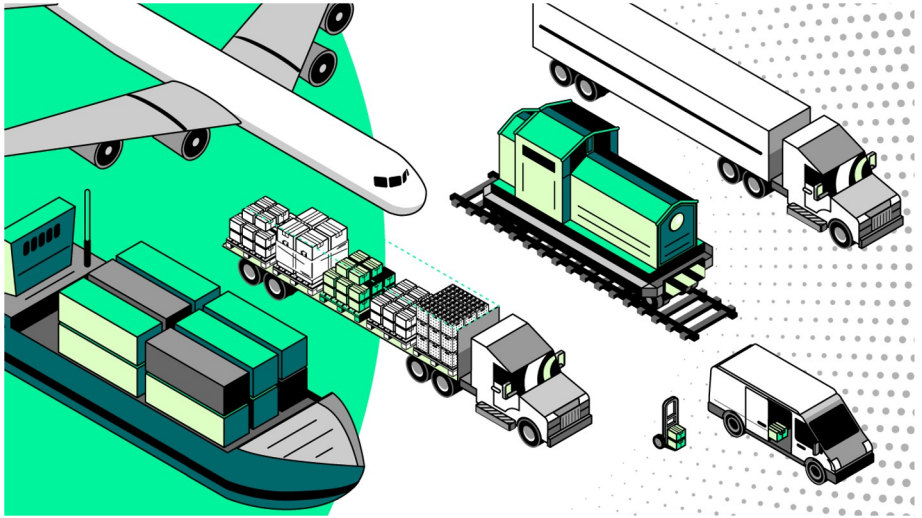
Trucks & buses: 8% of vehicles, but 35% of energy share in road transport (IEA, 2026)

Movement of People



Source: Audirac, Ivonne, et al. "Transportation and Mobility Modes." 2024.

Movement of Goods

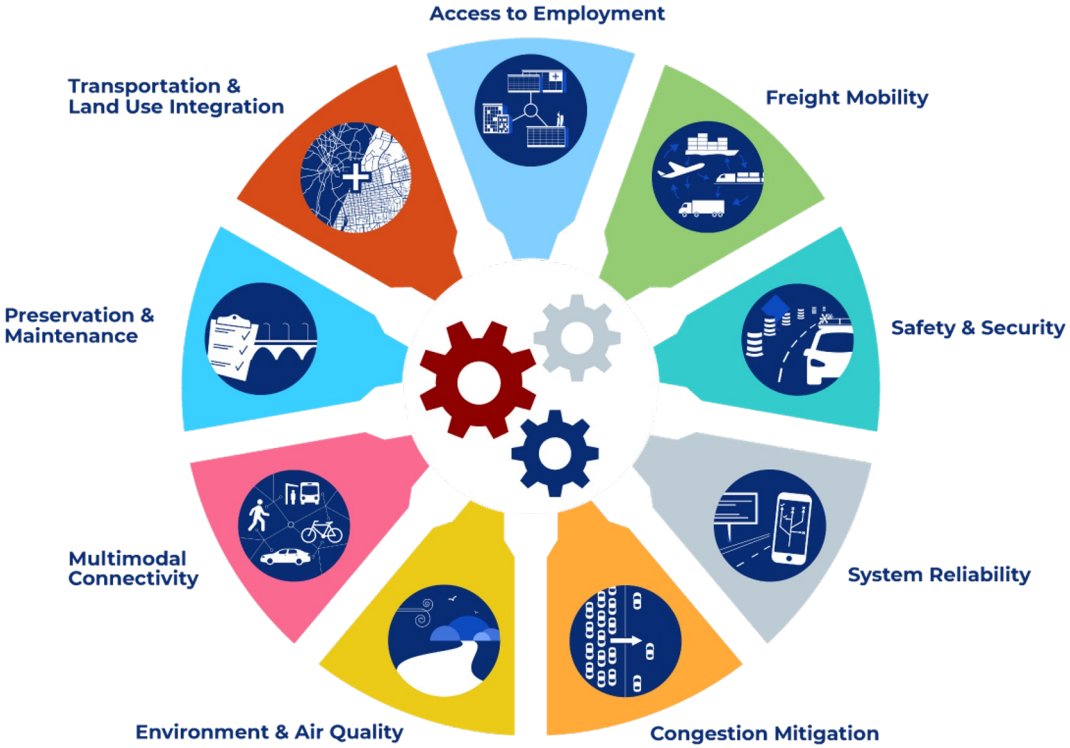


Source: RXO, 2026.

AI can be applied to various modes of transportation

Transportation System Goals

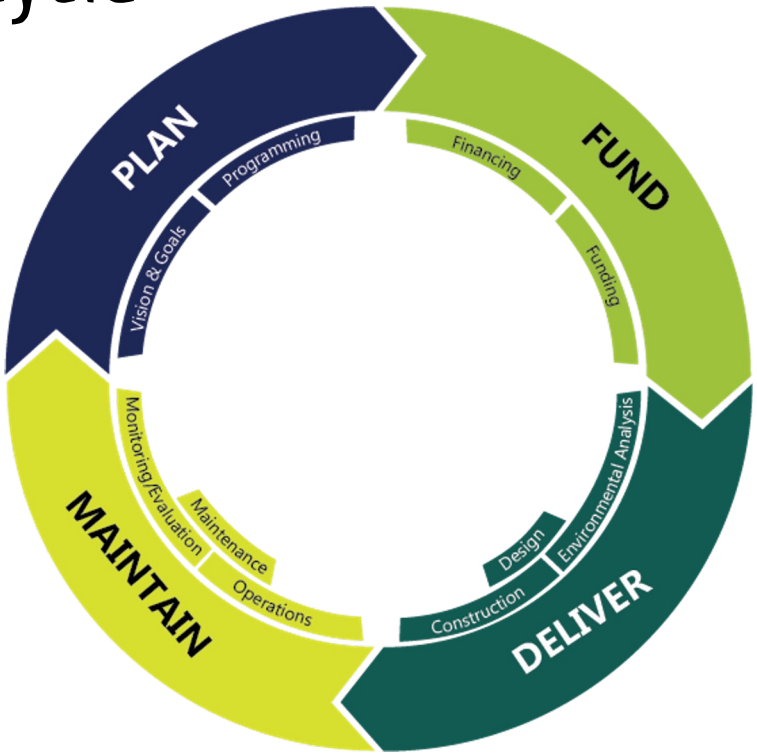
AI can be applied to various transportation goals



Source: Plan RVA. "What is Transportation Planning?", 2019.

Transportation Project Lifecycle

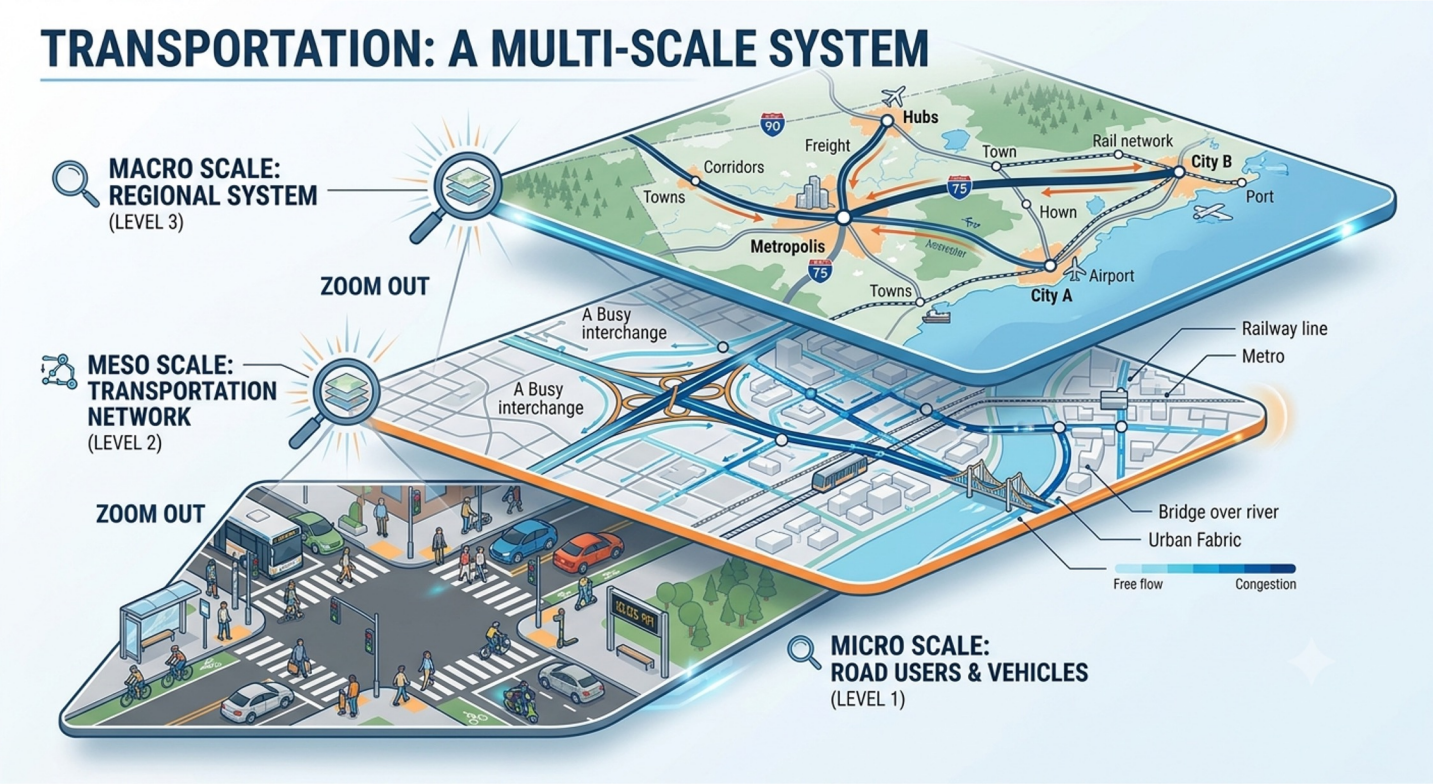
AI can be applied at various stages of a transportation project lifecycle



Source: US DOT. "Transportation Planning and Project Delivery." 2023.

Transportation as a Multi-Scale System

AI can be applied at various scales of a transportation system



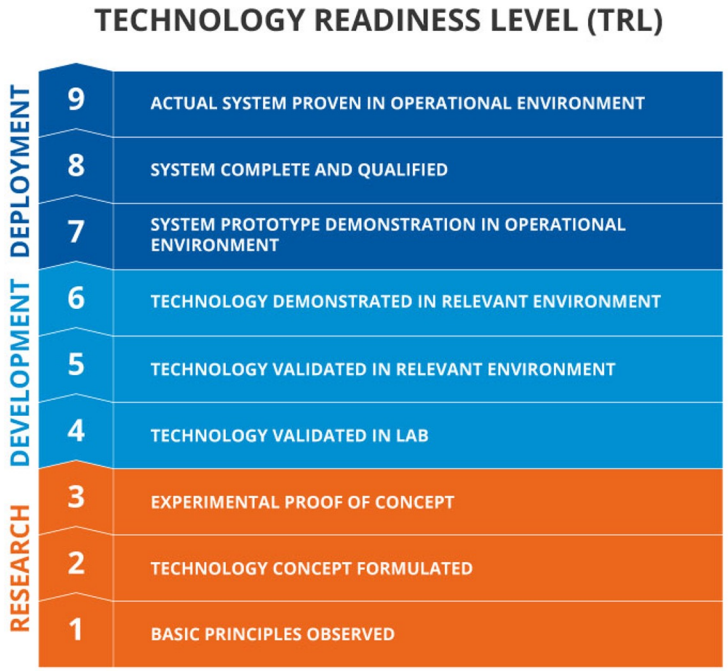
Source: Generated by Gemini 3 (Nano Banana), 2026-07-13.

AI and Technology Readiness Levels (TRL)

- Compares maturity of technologies
- Originally developed by NASA in the 1970s for space exploration technologies

Categories of use cases:

- Evaluating the maturity of AI technologies (LLMs, deep RL, etc.)
- Using AI to evaluate maturity of other technologies (AVs, EVs, etc.)



Source: TWI Global.

US DOT Federal Highway Administration, *What Is A Trl? - Technology Readiness Level Guidebook*, 2017, www.fhwa.dot.gov/publications/research/ear/17047/001.cfm.

Visibility & Decision-Making is Fragmented

Challenge: AI must be applied from the perspective of a stakeholder group

Adapted from S. S. R. Bonthu, et al., 2022.

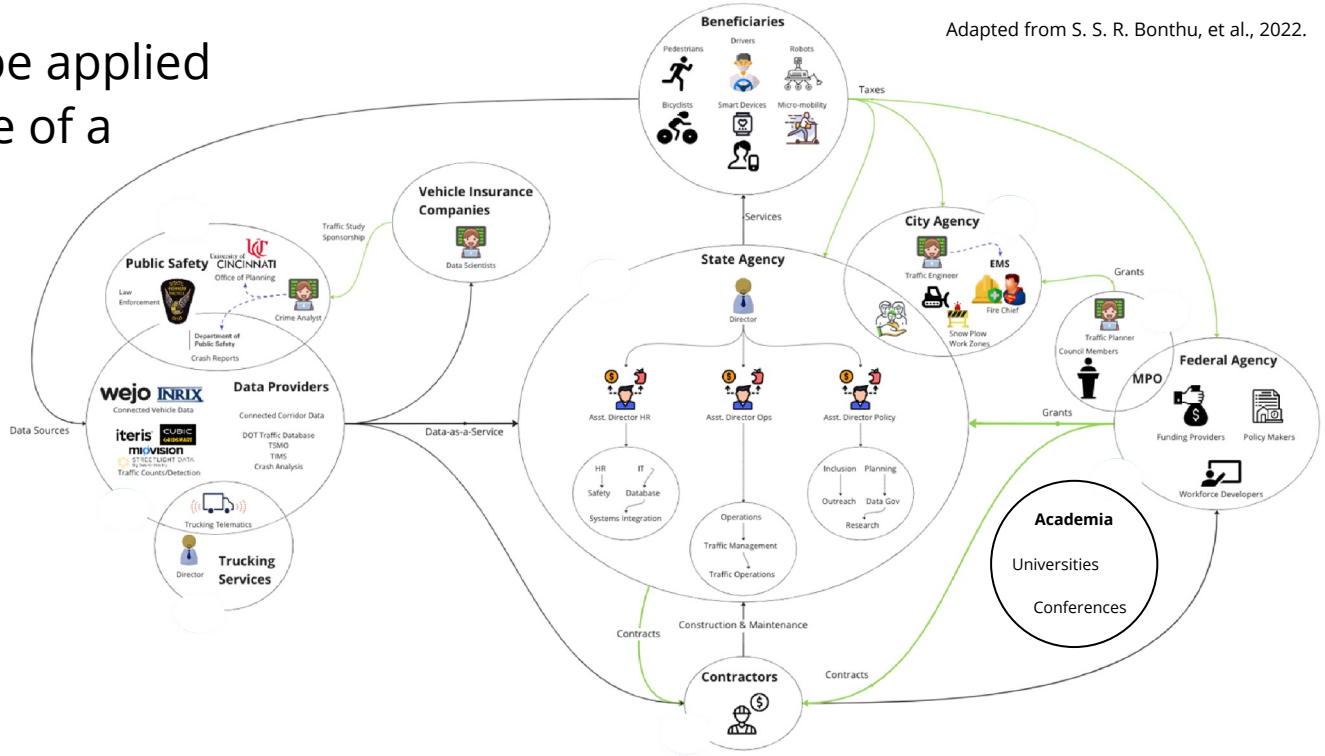


Figure 2. Complex transportation ecosystem with interview count highlighted across government agencies, data providers, and contractors.

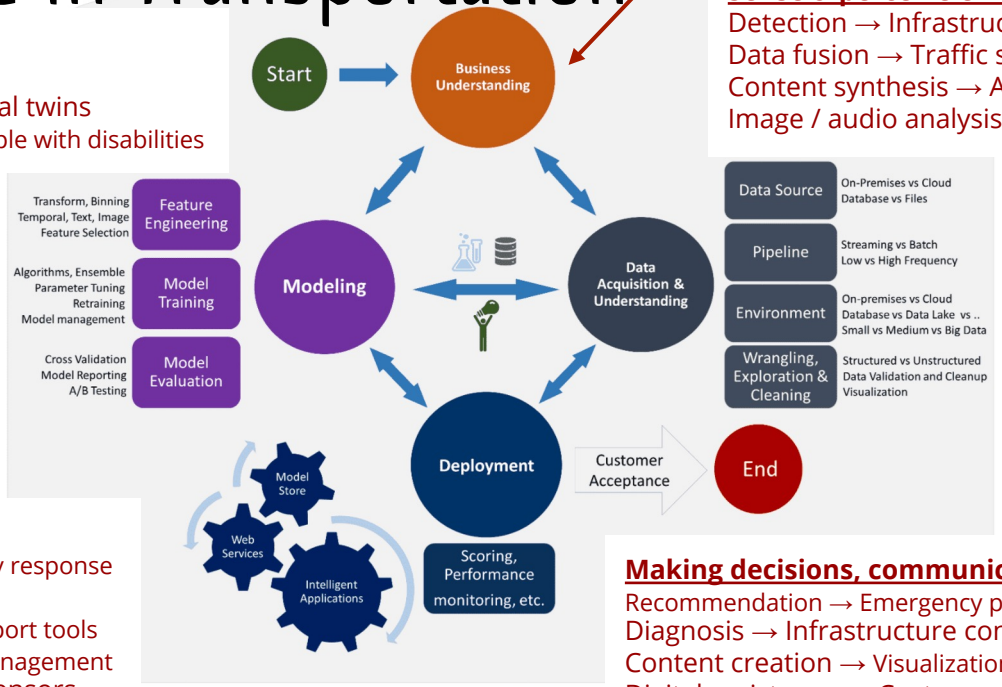
Data Science in Transportation

Pick a transportation mode, lifecycle stage, primary performance measure, scale, TRL, stakeholder group, etc.

Reason and analyze information
Prediction → Travel forecasts
Simulation → AI-assisted traffic digital twins
Personalization → Trip planning for people with disabilities

Sense & perceive environment
Detection → Infrastructure condition inspection
Data fusion → Traffic state estimation
Content synthesis → Analysis of public input
Image / audio analysis → Safety analysis

AI at various stages of a data science pipeline within a transportation use case



Source: Eric Mihail. "What is the Data Science Life Cycle?" 2026.

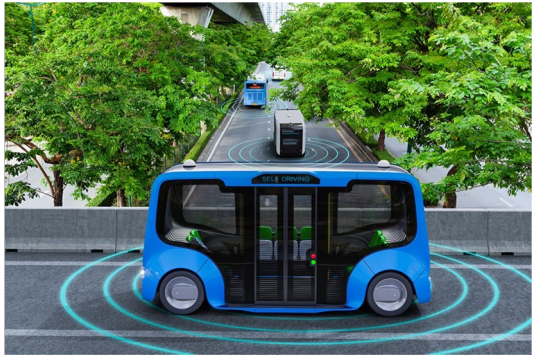
Learn from experience
Optimization → Routing for emergency response
Discovery → Innovative materials
Information retrieval → Decision-support tools
Performance improvement → Traffic management
Monitoring → Security cameras or sensors

Making decisions, communicate, & take actions
Recommendation → Emergency preparations for extreme weather
Diagnosis → Infrastructure condition inspection
Content creation → Visualizations of travel data
Digital assistance → Customer service

[1] Transportation Research Board Executive Committee, Transportation Research Board, and National Academies of Sciences, Engineering, and Medicine, Transforming Transportation: Leveraging the Power of Artificial Intelligence, Digitalization, and Automation. Washington, D.C.: National Academies Press, 2026, p. 29350. doi: 10.17226/29350.
[2] M. Vasudevan et al., “Identifying Real-World Transportation Applications Using Artificial Intelligence (AI)- Real-World AI Scenarios in Transportation for Possible Deployment,” FHWA-JPO-20-810, Jul. 2020. Accessed: Jan. 07, 2024. [Online]. Available: https://rosap.ntl.bts.gov/view/dot/50752.

Automation in Transportation

- Vehicular automation → SAE Level 4 car or bus
- Robotic automation → maintenance activities
- Process automation → crash reporting in the field



Public transport turns to robotics | Source: Sandalow, David B. et al., 2024.



Mobile cleaning and disinfection robot |Source: Fraunhofer IFAM, 2022.

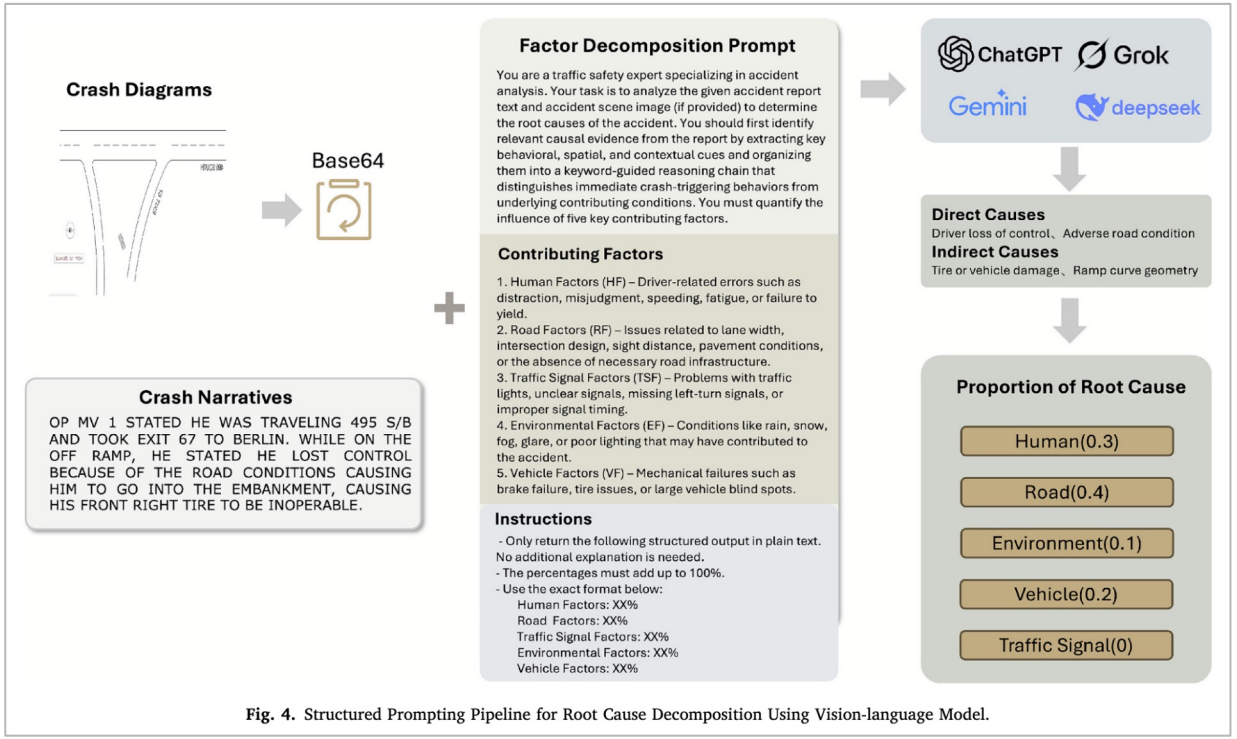
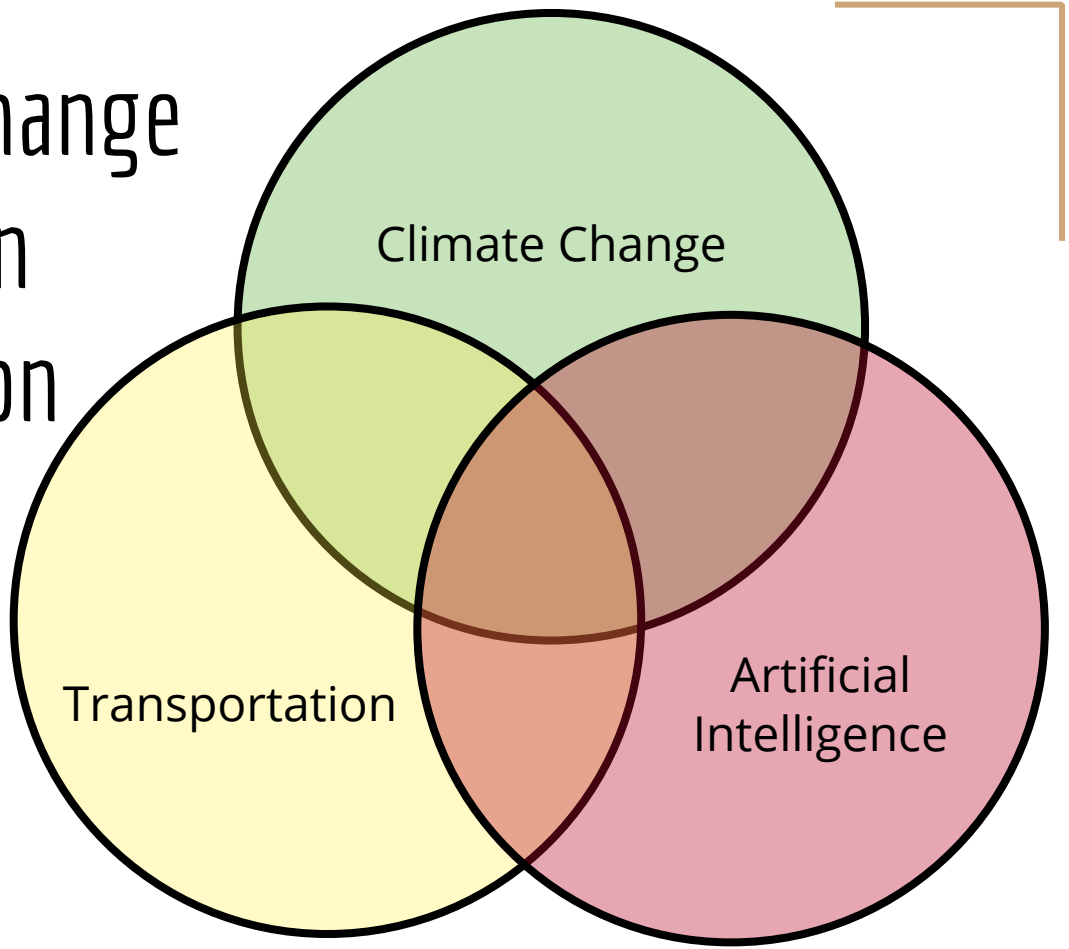


Fig. 4. Structured Prompting Pipeline for Root Cause Decomposition Using Vision-language Model.

Source: Wu, G., et al., "From crash reports to safer roads: a multimodal framework integrating vision-language models and street view analysis," 2026.

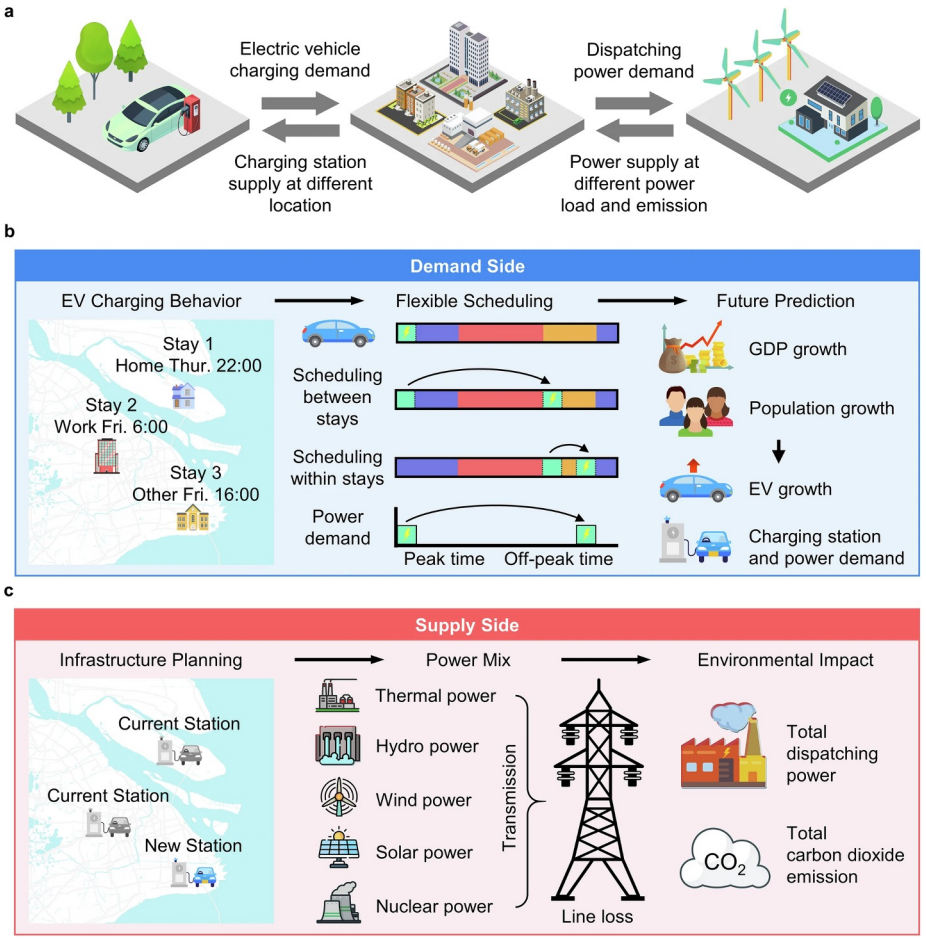
[1] Transportation Research Board Executive Committee, Transportation Research Board, and National Academies of Sciences, Engineering, and Medicine, Transforming Transportation: Leveraging the Power of Artificial Intelligence, Digitalization, and Automation. Washington, D.C.: National Academies Press, 2026, p. 29350. doi: 10.17226/29350.

AI for Climate Change Mitigation in Transportation



Vehicle Electrification

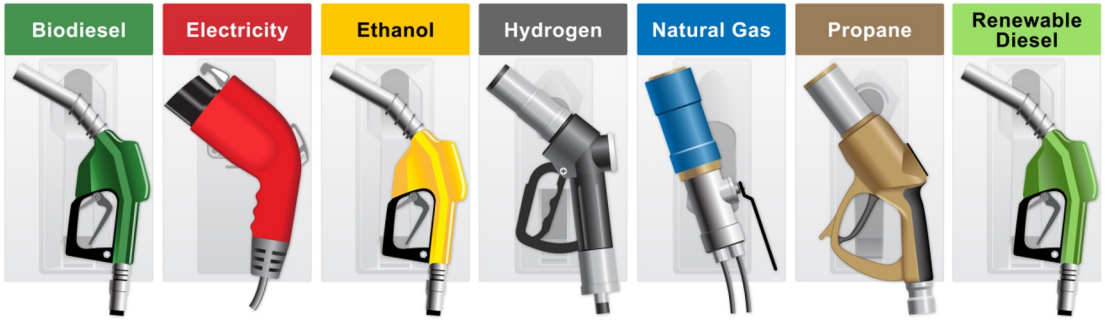
- **Materials discovery** for batteries & motors
  - See CCAI Virtual Summer School lecture on *AI for Accelerated Materials Science* by Francisco Martin-Martinez on Thu, Aug 13, 14:00–16:00 UTC
- **AI-assisted dis/charging** for energy management *[deep dive]*
  - Vehicle level (battery management)
  - Grid level (bidirectional charging, V2G/V2H/V2B)
- **Forecasting/digital twins** for battery health, recycling, and reuse



[1] Sandalow, David B. et al., “Artificial Intelligence for Climate Change Mitigation Roadmap (Second Edition),” Nov. 2024, doi: 10.7916/2J4P-NW61.
[2] Liao, Chenlei, et al. "Optimizing electric vehicle charging patterns and infrastructure for grid decarbonization." Commun. Sustain., 2026, doi:10.1038/s44458-026-00037-7.

Alternative Fuels

- Best fit: **heavy-duty**, long-distance, aviation/marine-adjacent use cases
- Fuels: biofuels, synthetic fuels (chemical), hydrogen, compressed/liquified natural gas (CNG/LNG)
- AI role: optimize fuel production, catalysts, electrolysis, fuel-cell design, combustion, logistics, and infrastructure planning
- Caveat: biofuels can have environmental impacts through land-use change; natural gas is transitional, not zero-carbon



Source: US Department of Energy. "Federal Fleet Alternative Fuel Resources." Energy, 2026.

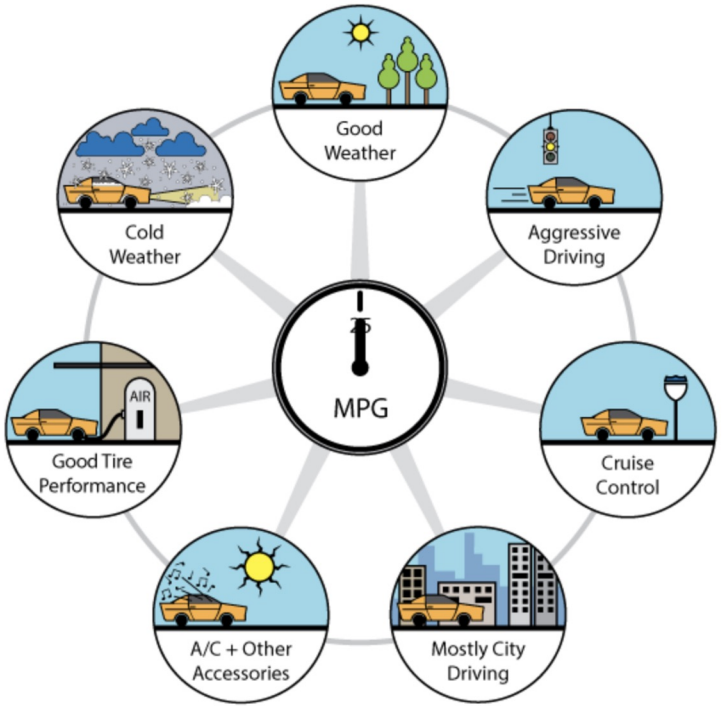
[1] Sandalow, David B. et al., “Artificial Intelligence for Climate Change Mitigation Roadmap (Second Edition),” Nov. 2024, doi: 10.7916/2J4P-NW61.

Vehicle Efficiency

AI for vehicle design + operation

- **Engineering design AI** can support:
  - combustion engine design
  - reducing vehicle weight or tire resistance
  - hybrid power-management strategies
  - aerodynamics: surrogate modeling and inefficient loading on freight trains
  - AI-assisted manufacturing
- **Operational AI** can support eco-driving, smoother traffic, platooning, and energy-aware control *[deep dive]*
- Caveat: efficiency gains can be offset by induced travel, especially with AVs

Factors that Affect Fuel Economy



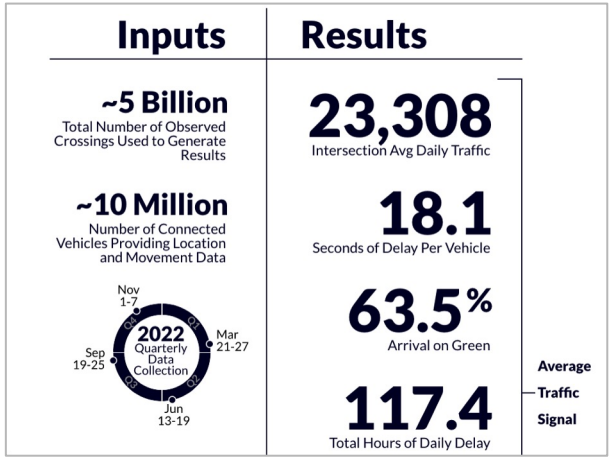
Source: US EPA, “Your Mileage May Vary,” 2026.

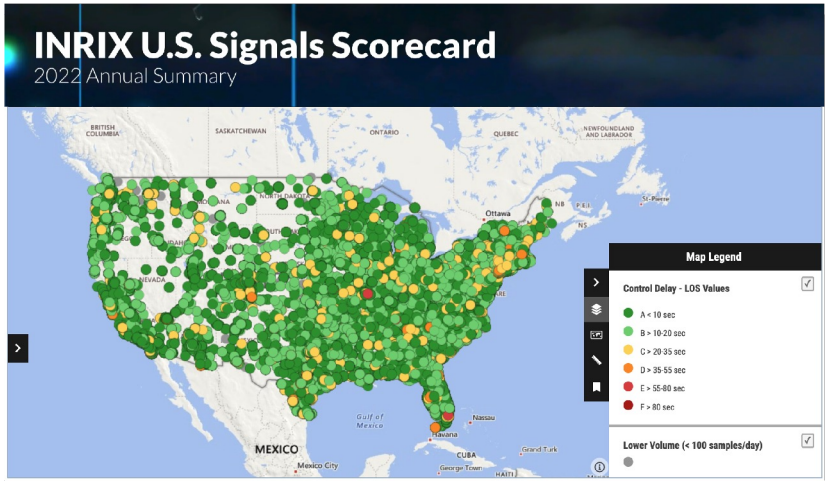
[1] D. Rolnick et al., “Tackling climate change with machine learning,” Jun. 2019, [Online]. Available: http://arxiv.org/abs/1906.05433v2

Intelligent Transportation Systems (ITSs)

AI for infrastructure and operations

- **Forecast congestion and anomalies** from sensors, GPS, cameras, and traffic data.
- **Optimize** signals, routing, incident response, transit schedules, and maintenance to reduce reduce delay, congestion, fuel use, and emissions.
- **AI-driven simulation** can evaluate charger siting, bike lanes, traffic policy, and energy demand.
- Challenges: data infrastructure - sensors, V2V/V2I, edge analytics, cloud integration
- Caveat: sensing and compute infrastructure has privacy, bias, and emissions costs.



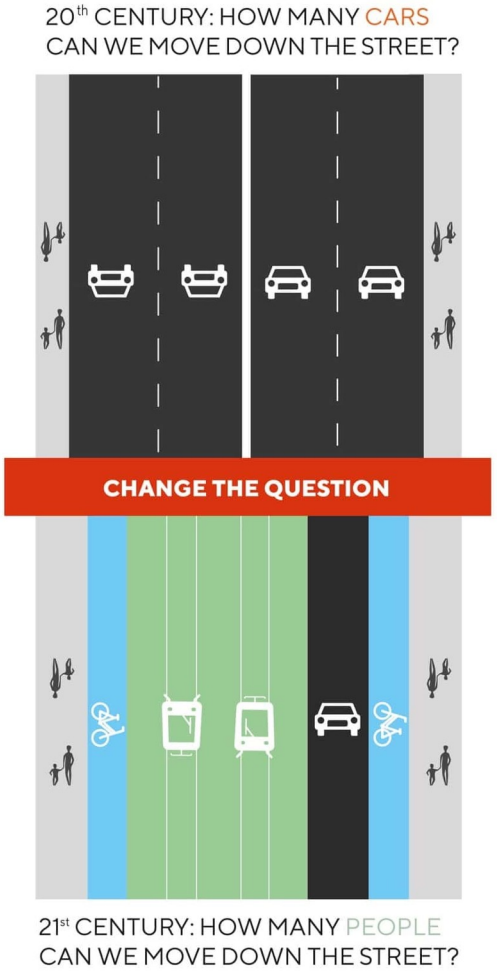


[1] Sandalow, David B. et al., “Artificial Intelligence for Climate Change Mitigation Roadmap (Second Edition),” Nov. 2024, doi: 10.7916/2J4P-NW61.
[2] INRIX U.S. Signals Scorecard: 2022 Annual Summary. INRIX. https://inrix.com/signals-scorecard/.

Modal Shifts

AI can make low-carbon modes easier to choose

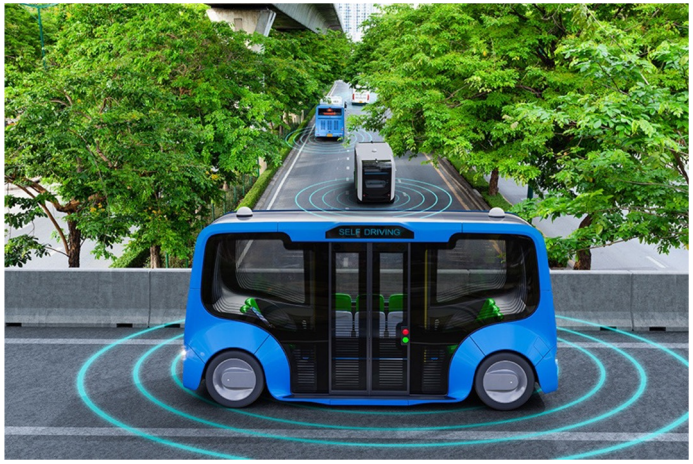
- Service and system planning
  a. Transit planning: **Predict transit demand**
  b. Multi-modal planning: **Integrate** walking, cycling, transit, rail, shared mobility, **autonomous public transit**, and micromobility *[deep dive]*
- Operations and maintenance
  a. Predictive maintenance and arrival-time prediction to improve reliability
  b. Use routing, pricing, and **recommendations** to shift trips.



Source: Copenhagenize Design Company/Mikael Colville-Andersen, 2018.

[1] Sandalow, David B. et al., “Artificial Intelligence for Climate Change Mitigation Roadmap (Second Edition),” Nov. 2024, doi: 10.7916/2J4P-NW61.

Autonomous Vehicles (AVs)



Climate promise or rebound risk?

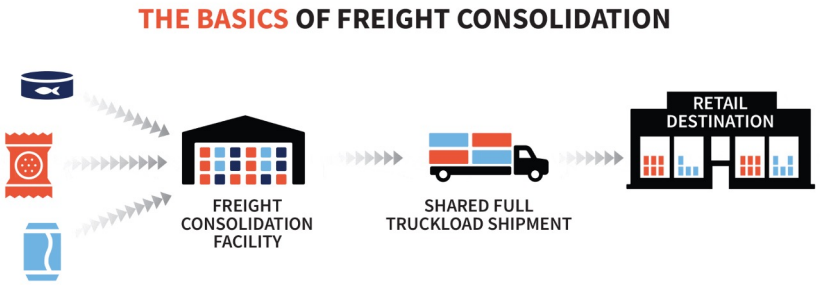
- Upside: eco-driving, platooning, smart parking, smoother traffic flow, shared electric fleets, first/last-mile transit.
- Risk: cheaper/easier travel increases VKT.
- Risk: AVs displace walking, cycling, and transit.
- Best climate case: **electric + shared + transit-complementary + governed**.
  - So far, consumers do not opt to share rides
- Bottom line: AVs are not inherently climate-positive.

[1] Sandalow, David B. et al., “Artificial Intelligence for Climate Change Mitigation Roadmap (Second Edition),” Nov. 2024, doi: 10.7916/2J4P-NW61.

Freight routing and consolidation

A high-leverage AI + OR use case → reduces empty miles, fuller vehicles

- **Consolidation** bundles partial shipments → fewer trips
- **Better routing** reduces empty backhauls, detours, idling, and dwell-time losses *[deep dive]*
- **AI use cases**: ETA prediction, demand forecasting, disruption prediction, supplier clustering, eco-routing, dynamic routing, optimization acceleration, and freight auction support



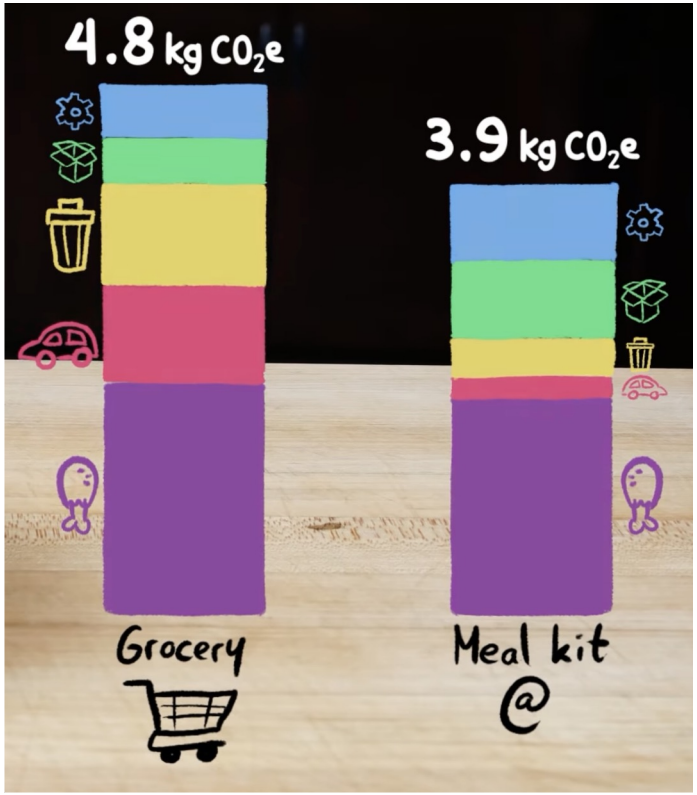
Source: Zipline Logistics, 2019.

[1] D. Rolnick et al., “Tackling climate change with machine learning,” Jun. 2019, [Online]. Available: http://arxiv.org/abs/1906.05433v2
[2] World Economic Forum, “Intelligent Transport, Greener Future: AI as a Catalyst to Decarbonize Global Logistics.” Jan. 2025.

Immobility solutions

AI for “Avoid” strategies: reducing the need to travel

- **Telepresence** can substitute for some commute and business travel
- **Accessibility models** can identify where detaily needs are reachable without driving
- **Delivery platforms** can consolidate trips
- **AI role**: demand prediction, accessibility mapping, batching, routing, and emissions-aware scheduling
- **Caveat**: saved time and convenience can rebound into more trips, more deliveries, or longer travel



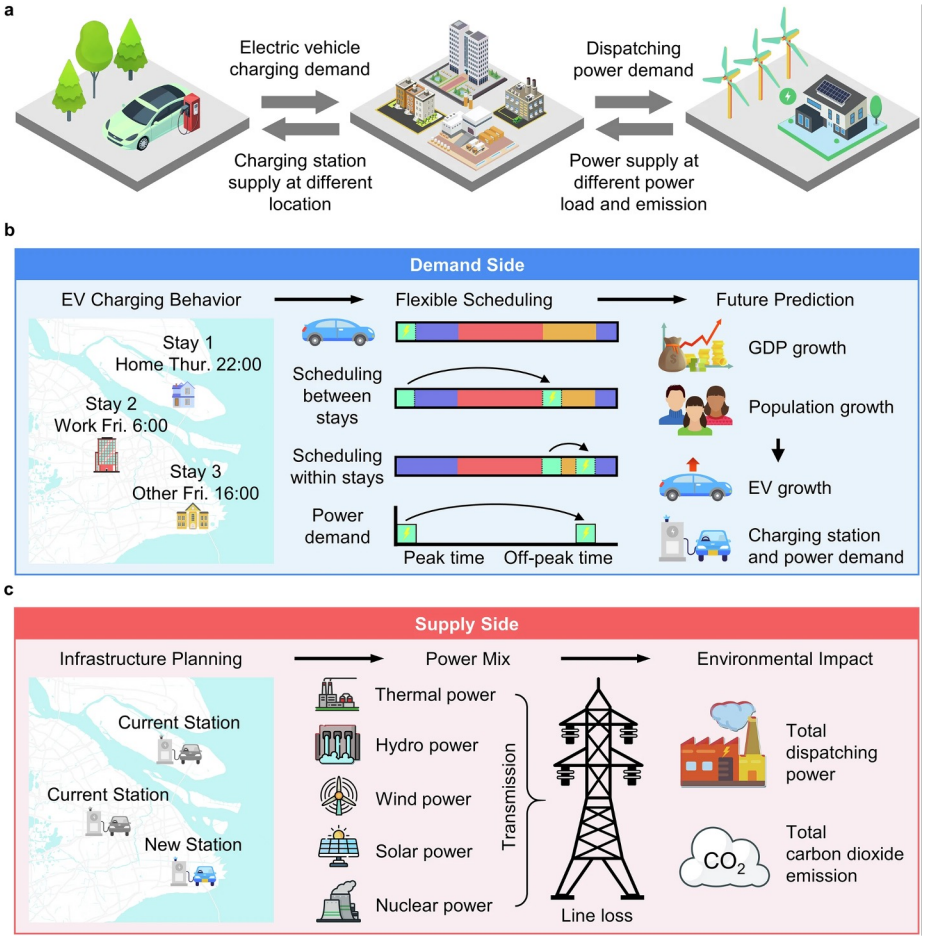
Meal kits can reduce emissions when delivery logistics replace individual shopping trips. Source: MinuteFood, 2023.

[1] P. Jaramillo and et al., “Transport,” in Climate Change 2022: Mitigation of Climate Change. Contribution of Working Group III to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change, 2024. doi: 10.1017/9781009157926.012.

[2] A. Nikolaeva, Y.-T. Lin, S. Nello-Deakin, O. Rubin, and K. C. von Schönfeld, “Living without commuting: experiences of a less mobile life under COVID-19,” Mobilities, vol. 18, no. 1, pp. 1–20, Jan. 2023, doi: 10.1080/17450101.2022.2072231.

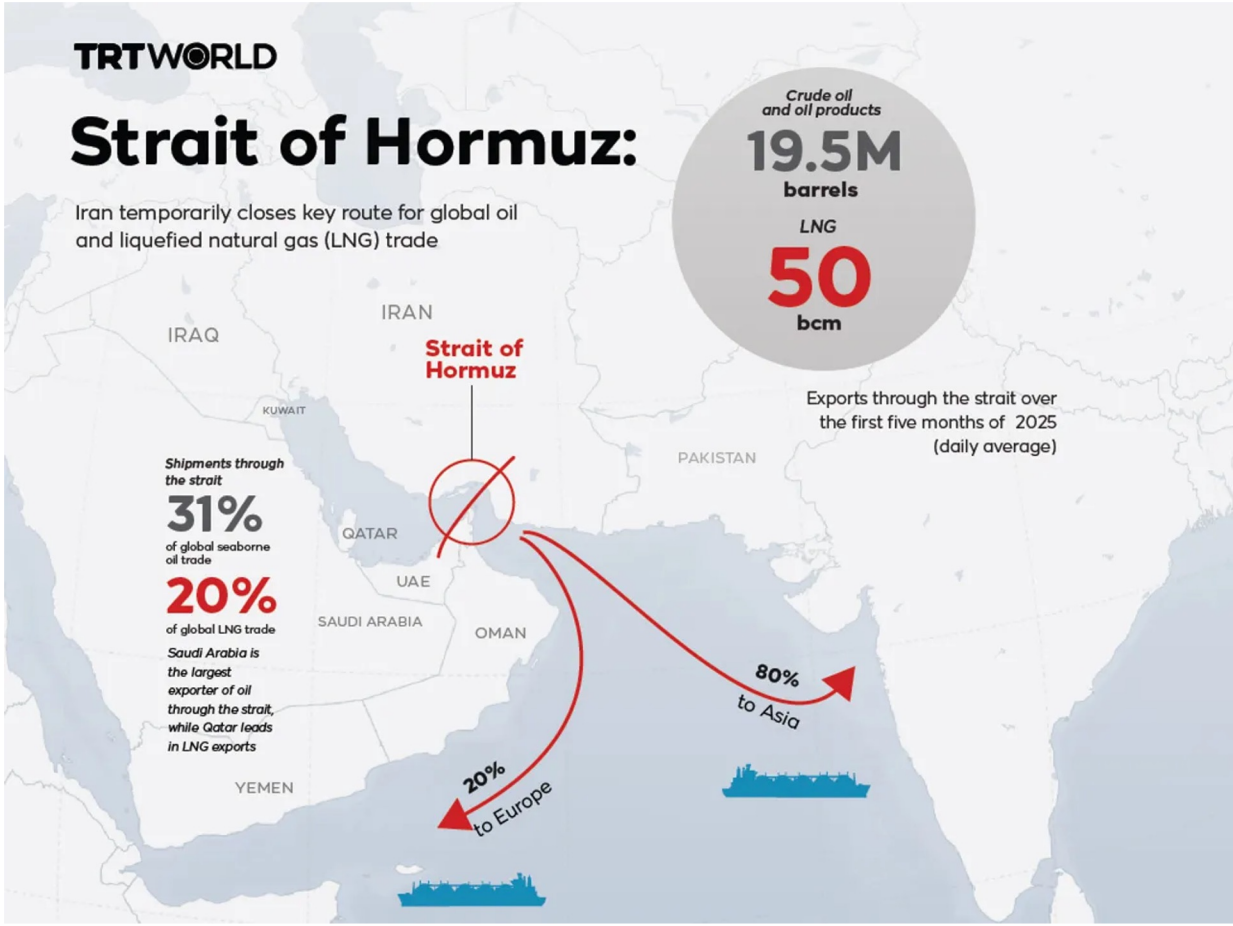
Deep Dive: Improve

AI for Electrification



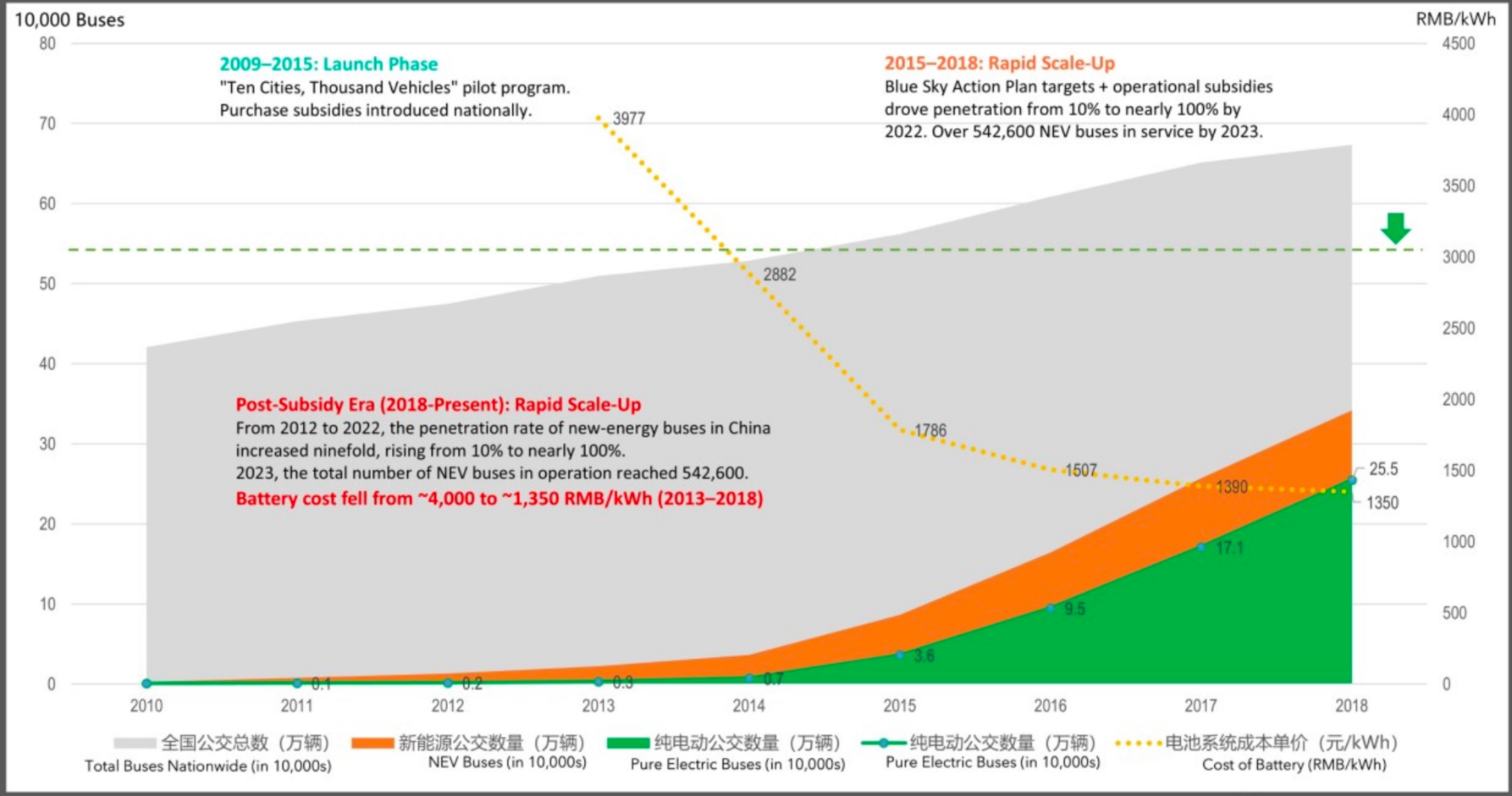
Why electrify?

1. Energy security



Source: TRT World, March 2, 2026

Electric Buses: Catalyzing China's Booming New Energy Vehicle Industry

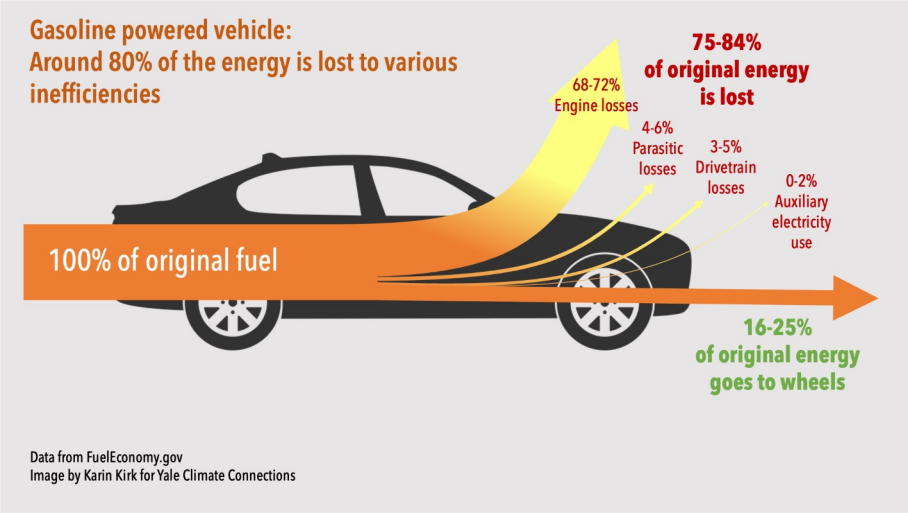


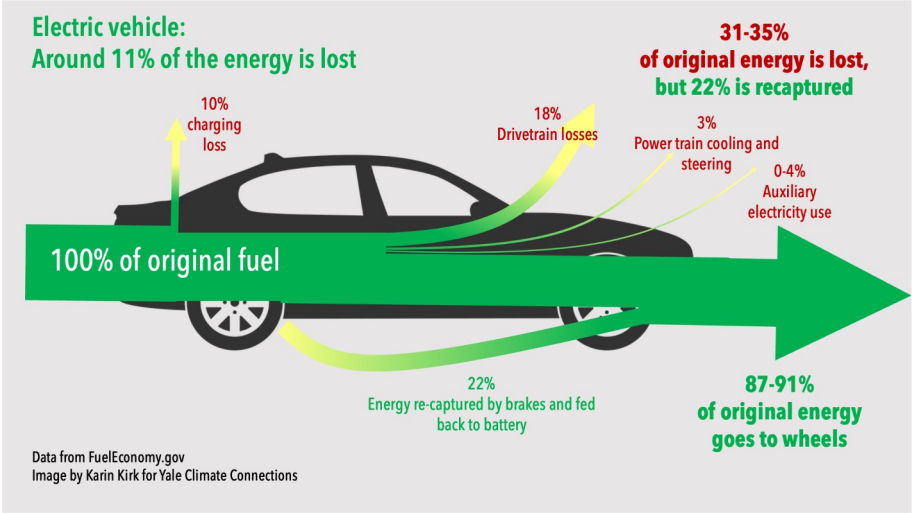
Slide credit: Daizong Liu, ITDP

ITDP | Institute for Transportation & Development Policy

Why electrify?

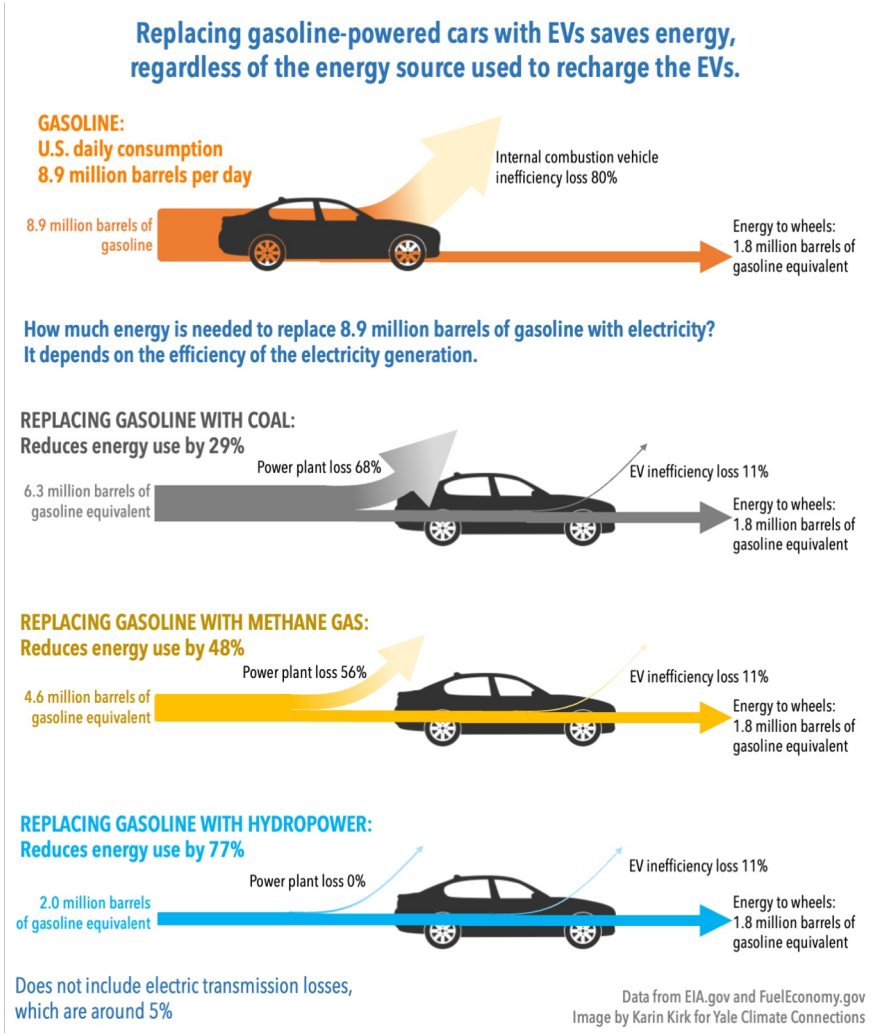
2. Reduce energy usage





Why electrify?

3. Take advantage of renewables



Caveats to electrification

- Up to 92% lifecycle carbon emissions reduction vs ICE vehicles [1]
  - *When manufactured using and powered by **clean electricity and are recycled***
- Operational emissions
  - Grid isn't clean yet
  - Projected **increases in travel demand** can offset emissions reduction
  - **Continued congestion, high land consumption** for roads and parking
- Embodied emissions and impacts
  - Global vehicle **fleet turns over on a 15-20 year cycle**
  - **Embodied carbon** required to produce the EVs and charging infrastructure shifts the problem to another sector Industry
  - Substantial innovation & effort is needed to transition to a clean manufacturing
  - Large demand for **critical minerals** (has its own sustainability issues)

[1] "Lifecycle Emissions Study: EVs vs. Conventional Vehicles." Great Plains Institute, 1 July 2025, betterenergy.org/electric-vehicle-lifecycle-analysis.

Scenario projections

Current Policies Scenario | Stated Policies Scenario

EV market | EV charging | EV energy impact

Cars | 2 and 3 wheelers | Vans | Buses | Trucks

EV sales projections

EV sales, cars

2025
21
million sales

2035
49
million sales

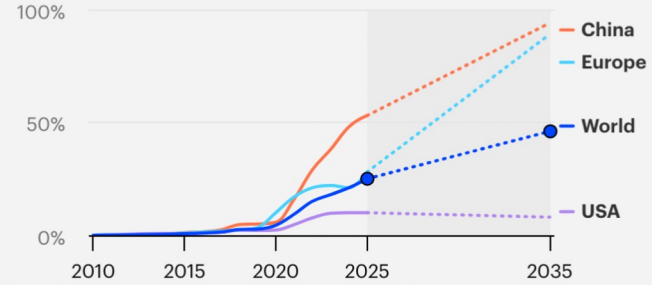
EV fleet projections

EV stock, cars

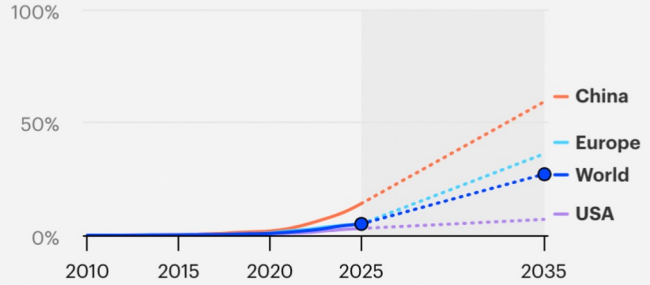
2025
75
million vehicles

2035
450
million vehicles

EV sales share, cars

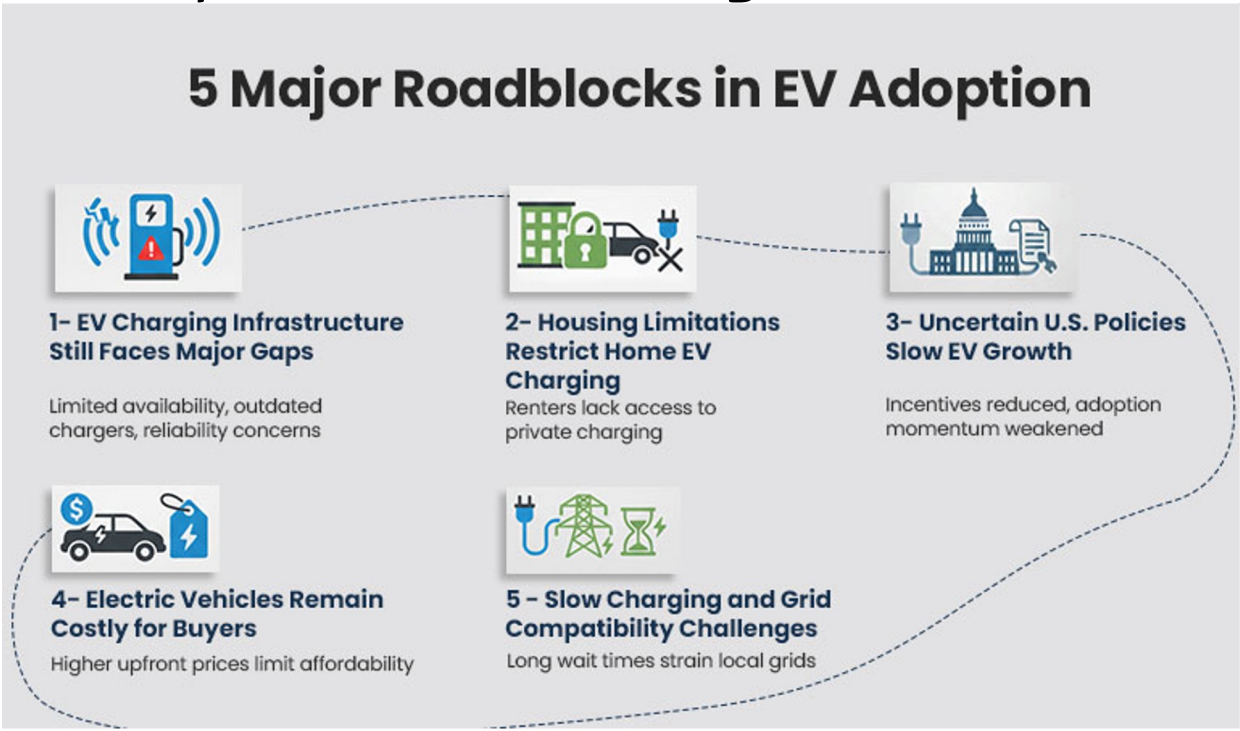


EV stock share, cars



"Global EV Data Explorer – Data Tools - IEA." IEA, May 2026, www.iea.org/data-and-statistics/data-tools/global-ev-data-explorer.

Vehicle Electrification Challenges in the US

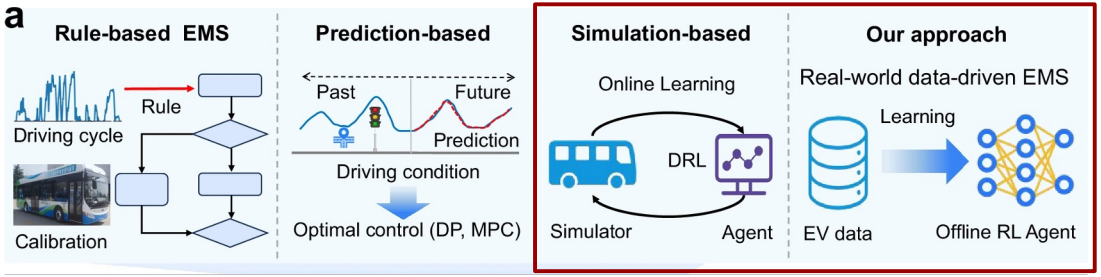


Source: SolarSME, 2026

[1] M. Liu et al., "Tariffs on electric vehicles deepen woes of U.S. electrification stagnation," npj Clim. Action, 2026, doi: 10.1038/s44168-025-00330-6.

Battery efficiency and lifespan

- Extend driving range and battery lifespan by allocating energy with reinforcement learning (RL)
- This approach could take advantage of China's EV monitoring platform, which collects real-time operational data from over 20 million EVs



What makes the problem suitable for deep RL

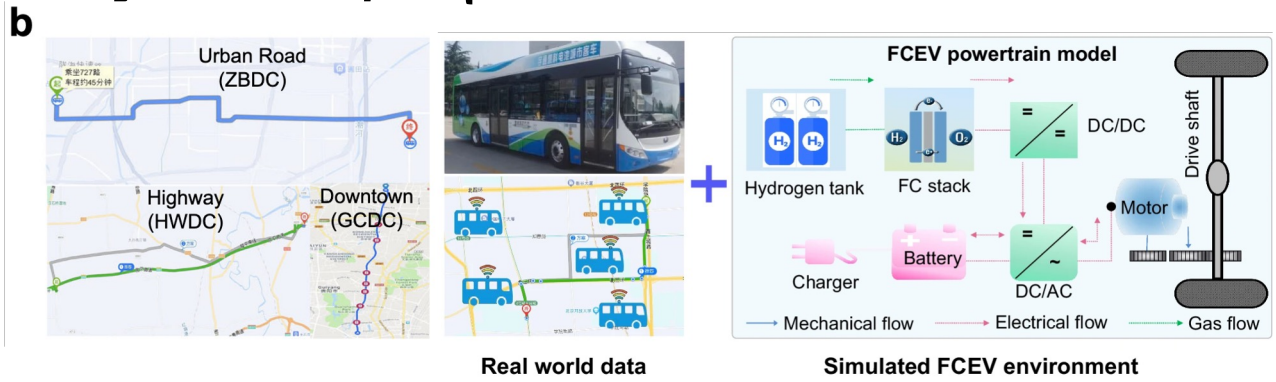
- Dynamic traffic conditions → sequential decision-making
- Complex hybrid powertrains (batteries, fuel cell, ICE combos) → learn from data
- Real-time application → fast inference of ML models

[1] X. Hu et al. Reinforcement Learning for Hybrid and Plug-In Hybrid Electric Vehicle Energy Management: Recent Advances and Prospects. IEEE Industrial Electronics Magazine 13, 16-25 (2019). https://doi.org/10.1109/MIE.2019.2913015.

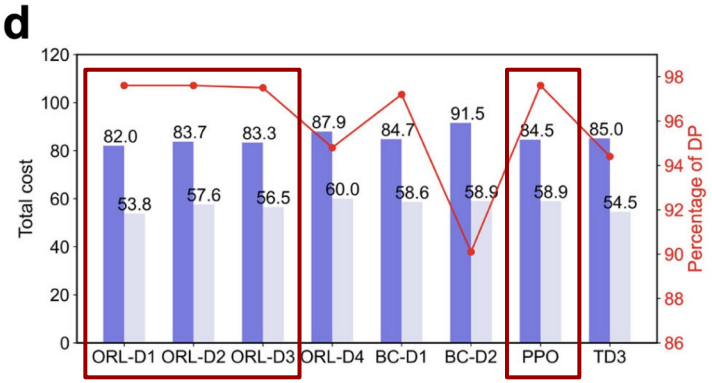
[2] Y. Wang, J. Wu, H. He, Z. Wei, and F. Sun, "Data-driven energy management for electric vehicles using offline reinforcement learning," Nat Commun, vol. 16, no. 1, p. 2835, Mar. 2025, doi: 10.1038/s41467-025-58192-9.

Battery efficiency and lifespan

Data-augmented simulation



RL methods achieve near-optimal performance (computed using dynamic programming)



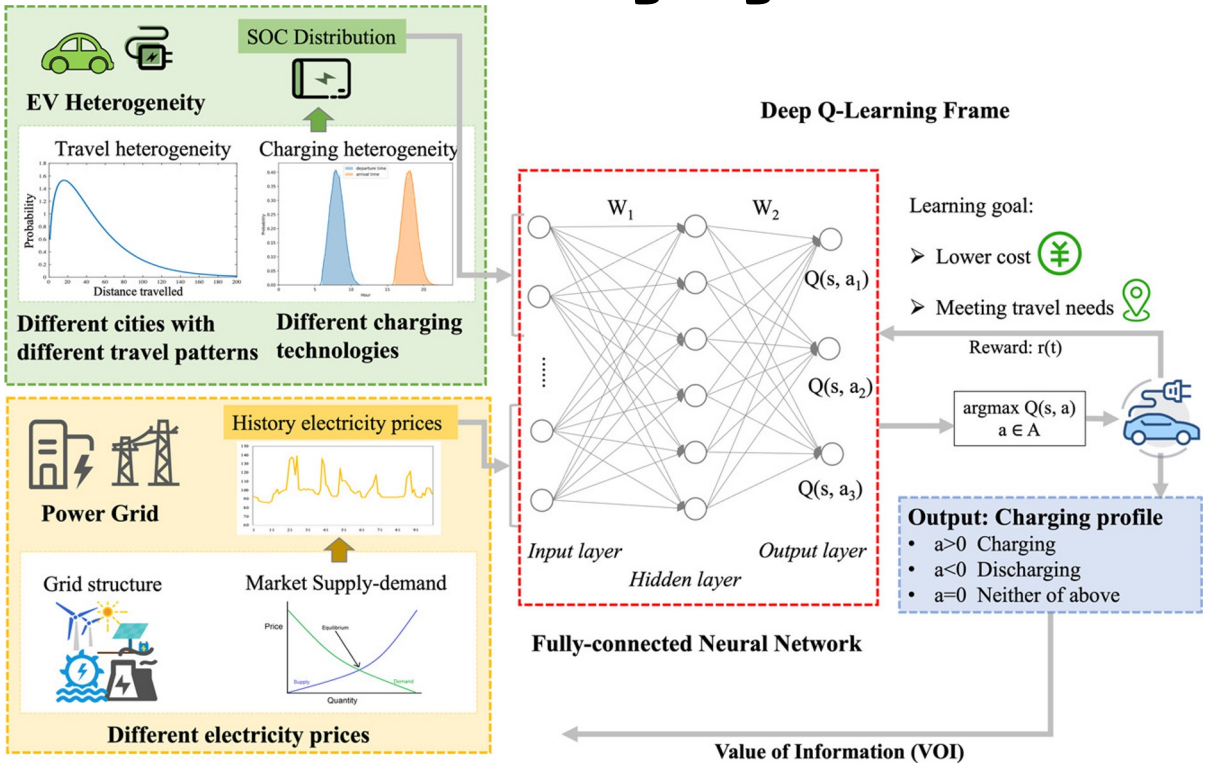
Result: RL reduces total cost by 13% over the stock controller

Caveat: stock method does not account for battery lifespan whereas RL does (penalizes *power slope*)

[1] Y. Wang, J. Wu, H. He, Z. Wei, and F. Sun, “Data-driven energy management for electric vehicles using offline reinforcement learning,” Nat Commun, 2025.

Smart Charging / Bidirectional Charging (V2G)

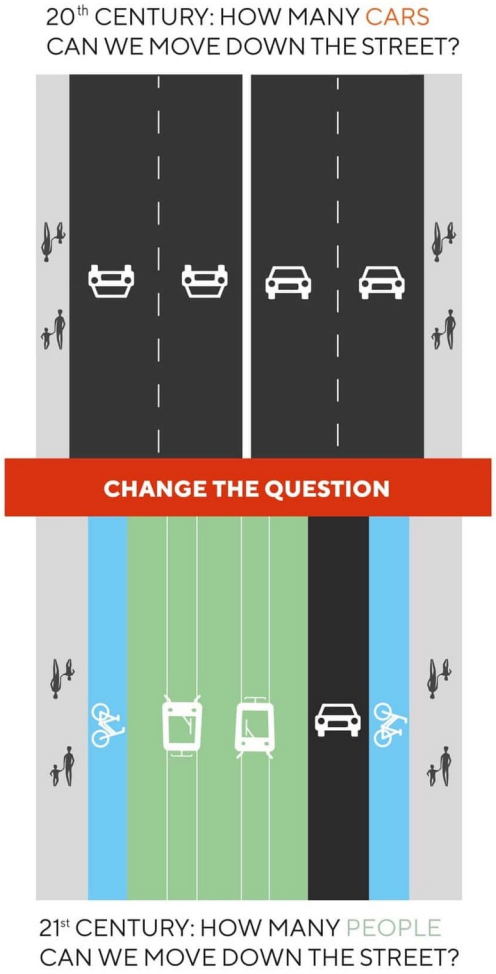
- EVs can act as distributed storage for urban load shifting
- Use deep Q-learning (DQN) to learn dis/charging policies under prices and mobility constraints
- Uses 1mil km of Chinese EV driving data
- DQN policy saved 98% in electricity cost vs a charging as-soon-as-possible method (weak baseline)



Hao, Xu, et al. "A V2G-oriented reinforcement learning framework and empirical study for heterogeneous electric vehicle charging management." Sustainable Cities and Society, vol. 89, 1 Feb. 2023, p. 104345, doi:10.1016/j.scs.2022.104345.

Deep Dive: Shift

AI for Modal Shift



Source: Copenhagenize Design Company/Mikael Colville-Andersen, 2018.

Why bike? (Copenhagen, Denmark)





Source: Copenhagenize Design Company/Mikael Colville-Andersen, 2018.

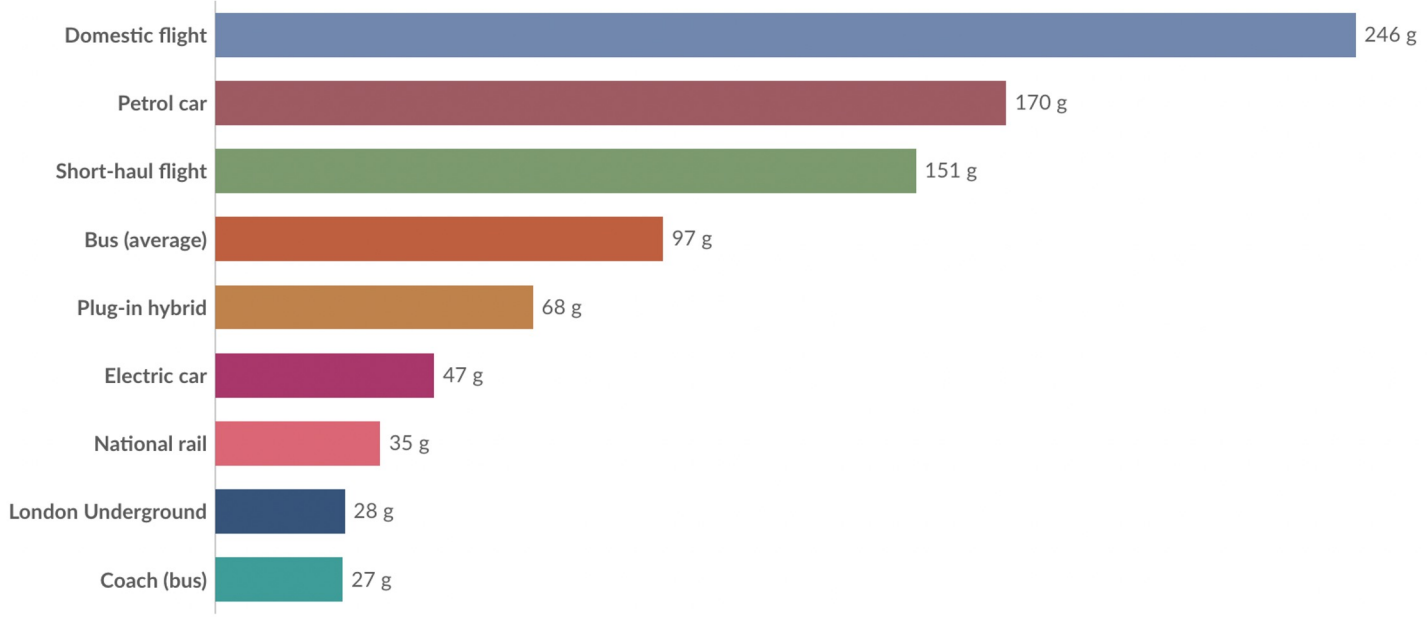
Carbon footprint of travel per kilometer, 2022

The carbon footprint of travel is measured in grams of carbon dioxide-equivalents per passenger kilometer. This includes the impact of increased warming from aviation emissions at altitude.

Our World in Data

Table | Bar

Edit countries and regions



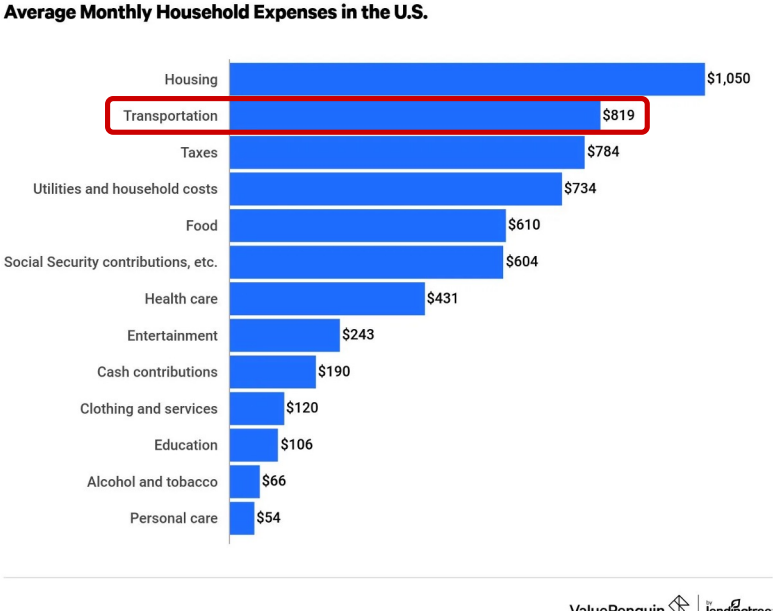
Data source: UK Government, Department for Energy Security and Net Zero (2022) – Learn more about this data

Note: Official conversion factors used in UK reporting. These factors will vary across countries depending on energy mix, transport technologies, and occupancy of public transport. Data for aviation is based on economy class.

OurWorldinData.org/transport | CC BY

Affordability & access

In 2024, **45.5% of U.S. households** did not earn enough to make ends meet.



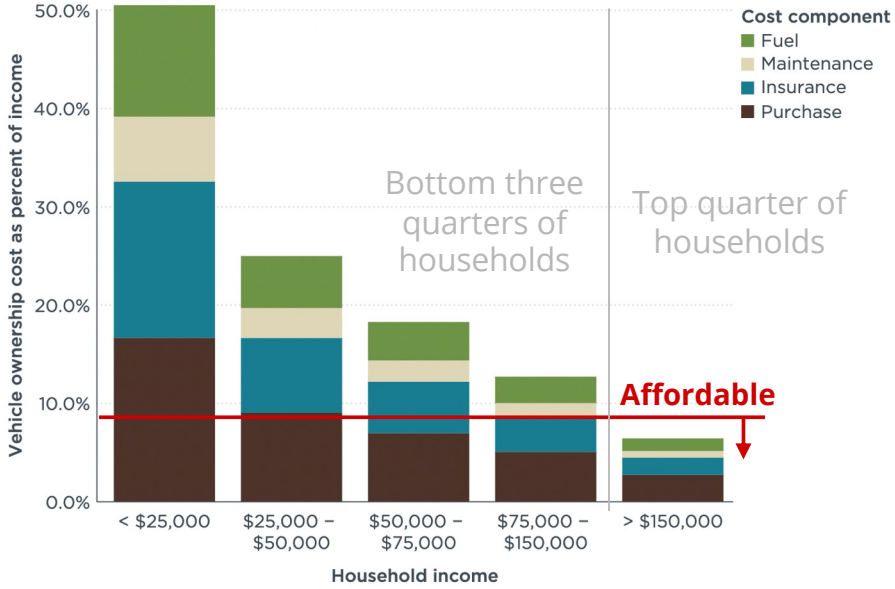


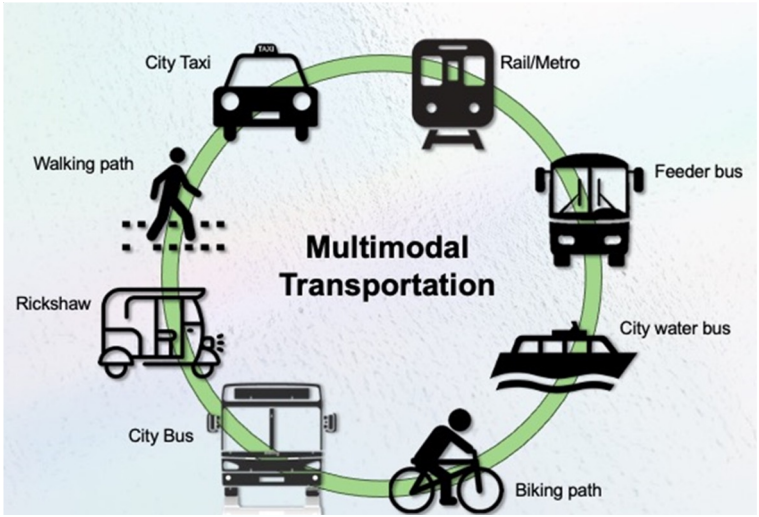
Figure 1. Total cost of vehicle ownership as percent of income, by annual household income.

[1] "States of Affordability: A series on where and why US households struggle to make ends meet | Brookings." Brookings, 24 June 2026, www.brookings.edu/articles/states-of-affordability-a-series-on-where-and-why-us-households-struggle-to-make-ends-meet.

[2] Bauer, Gordon, Chih-Wei Hsu, and Nic Lutsey. "When might lower-income drivers benefit from electric vehicles? Quantifying the economic equity implications of electric vehicle adoption." International Council on Clean Transportation. Working Paper 6 (2021).

Multi-modal urban mobility

- **Definition**: An approach to transport that supports all modes people use to get around (private vehicles, walking, biking, transit, shared mobility, combinations of modes, etc.).
- **Strategies**
  - Public transit
  - Street design: bike lanes, road diets, transit signal priority
  - Congestion pricing (Bloomberg on NYC congestion pricing)
  - Real-time trip planning & wayfinding
  - Mobility-as-a-service (MaaS), incl. integrated payment
- **Why it is hard**
  - *Physical integration:* transfers must be fast, safe, convenient
  - *Institutional coordination:* many public agencies and private operators
  - *Data interoperability:* schedules, fares, routing, and real-time updates must connect
  - *Business model alignment:* who pays, who benefits, who shares data?
  - *Equity and privacy:* seamless service should not exclude low-income or data-poor users



Source: Audirac, Ivonne, et al. "Transportation and Mobility Modes." 2024.

[1] StreetLight, "Multimodal Transportation: What Is It, and How Does It Benefit Everyone?", 2024, www.streetlightdata.com/what-is-multimodal-transportation.

AI for agent-based transportation simulation

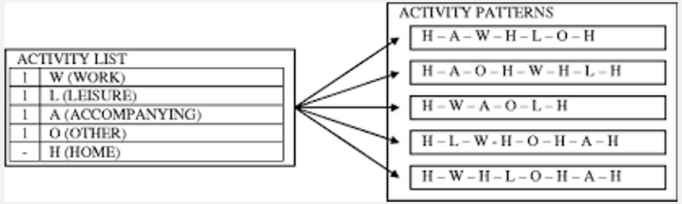
Travel Demand Forecasting

Travel demand forecasting is critical to the evaluation and planning of transportation systems

- **Why**, **when** and **how** people travel?

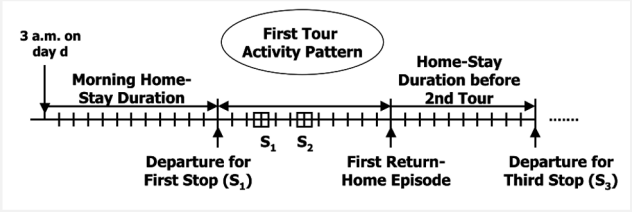
Why

Pic: Bifulco et al.



When

Pic: Pinjari and Bhat

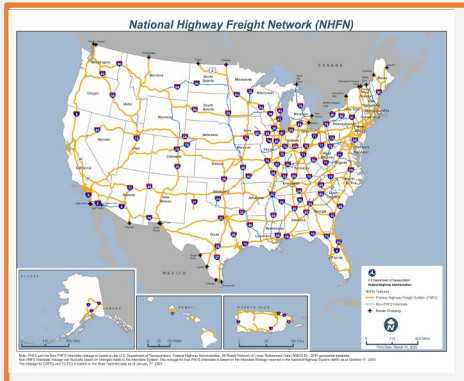


How

Pic: Train

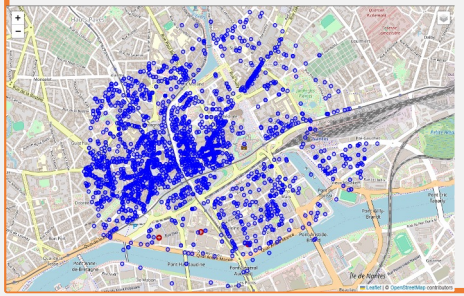
$$U_c = \alpha T_c + \beta M_c + \varepsilon_c$$
$$U_b = \alpha T_b + \beta M_b + \theta_b Y + k_b + \varepsilon_b$$

supports



System Modeling

Pic: FHWA



Dynamics Simulation

Pic: Matsim

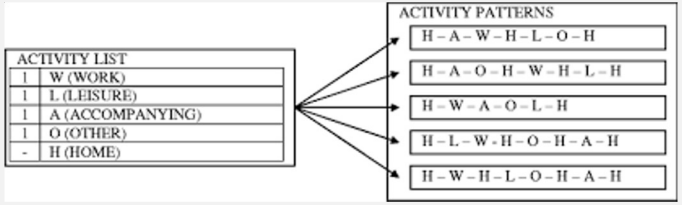
Slides adapted from Tianming Liu (tianmliu@umich.edu)

Impact of Travel Demand Forecasting

Travel demand forecasting **drives critical planning and infrastructure investment decisions** of public agencies from federal level to local level.

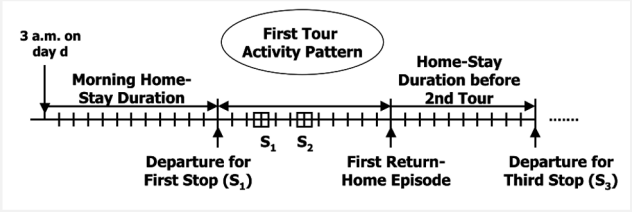
Why

Pic: Bifulco et al.



When

Pic: Pinjari and Bhat



How

Pic: Train

$$U_c = \alpha T_c + \beta M_c + \varepsilon_c$$

$$U_b = \alpha T_b + \beta M_b + \theta_b Y + k_b + \varepsilon_b$$

Drives

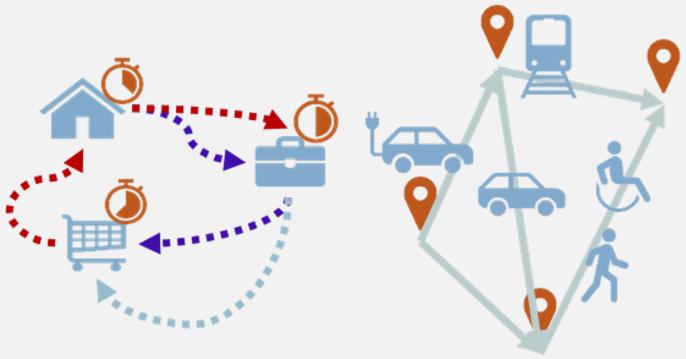


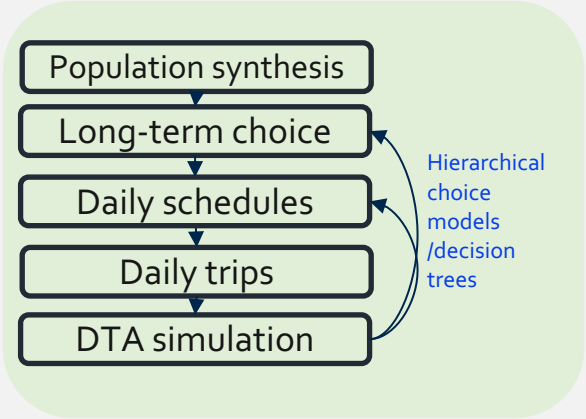


Slides adapted from Tianming Liu (tianmliu@umich.edu)

Activity-based Modeling of Travel Demand

- The-state-of-the-art paradigm of travel demand modeling
- Recent efforts primarily leverage agent-based simulation





Agents follow hardcoded condition-action rules to schedule daily activities and make travel plans. They can learn, adapt, and improve their interactions with other agents as well as their dynamic environment.

Limitations of Existing Approaches

- The existing limitations mainly related to the **assumptions** and **complexity** of setting up a good model

Necessity of model assumptions

Example: MNL model

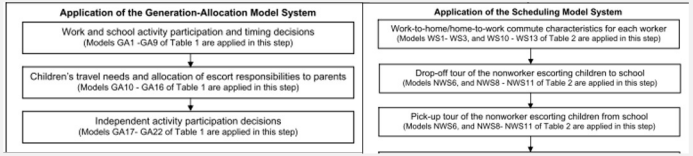
Assumption 1:
- We assume that the error terms each follow the Type-2 extreme value distribution (Gumbel distribution):
  - $\epsilon_{1n} \sim Gumbel(\eta, \mu)$
  - $\epsilon_{2n} \sim Gumbel(\eta, \mu)$

Assumption 2:
- We assume that ϵ_{1n} and ϵ_{2n} are independent and identically distributed (i.i.d.) across individuals, and independent of the attributes x_n.

Models require *a-priori* assumptions to work

Complexity in model calibration

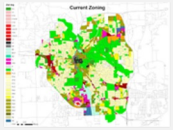
Example: a typical ABM



Overall, **49 models** have to be calibrated in modeling travel behavior

Complexity in data demand











A large amount of data is needed to set up the model (otherwise parameters are borrowed)

LLM Agents and Their Applications in Simulation

Simulacra of Human Behavior



Figure 1: Generative agents are believable simulacra of human behavior for interactive applications. In this work, we demonstrate generative agents by populating a sandbox environment, reminiscent of The Sims, with twenty-five agents. Users can observe and intervene as agents plan their days, share news, form relationships, and coordinate group activities.

Gemini

Qwen3

role-play



J. S. Park, et al., "Generative agents: Interactive simulacra of human behavior," in Proceedings of the 36th annual acm symposium on user interface software and technology, 2023.
Grossmann, et al., AI and the transformation of social science research, Science, 2023, 380 (6650).

Slides adapted from Tianming Liu (tianmliu@umich.edu)

LLM as a Proxy of Human Behavior

- Key hypothesis: LLMs have the potential to act as "silicon samples"
- Main reason is that LLM has three key properties:

Imitation in learning



Human-like Interaction



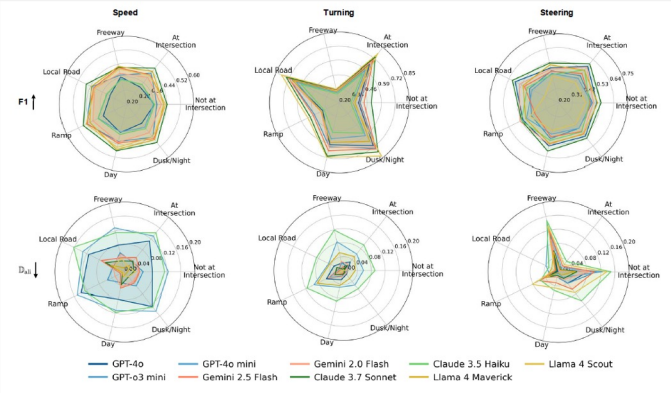
Instruction-following and role-play



Critical questions: **how much do they align with human travel behavior**?

* Grossmann, et al., AI and the transformation of social science research, Science, 2023, 380 (6650).
** Hutson, M., Can AI chatbots replace human subjects in behavioral experiments. Science, 2023, 381(6654).

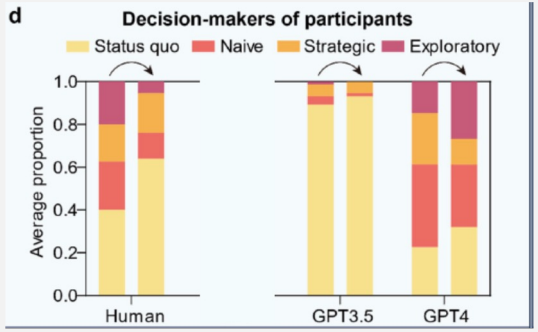
LLMs are Human-like but not Human-authentic



Autonomous driving: better aligned with aggressive drivers

Purpose	Income Elasticity			
	USDOT	Binsuwadan et al. (2023)*	Shires and de Jong (2009)**	GPT-4o
Commute	1	0.37	0.67	0.24
Business	1	0.53	0.47	0.21
Leisure	1	0.53	0.52	0.22
Personal	1	0.53	0.52	0.22

Value of time: lower elasticities

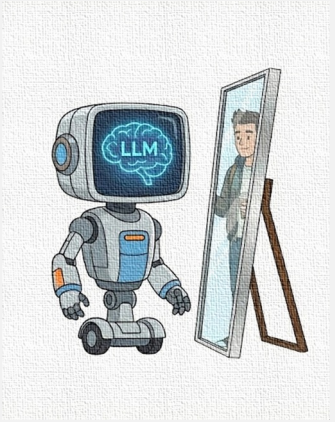


Congestion games: Learning route choice adaptation in traffic



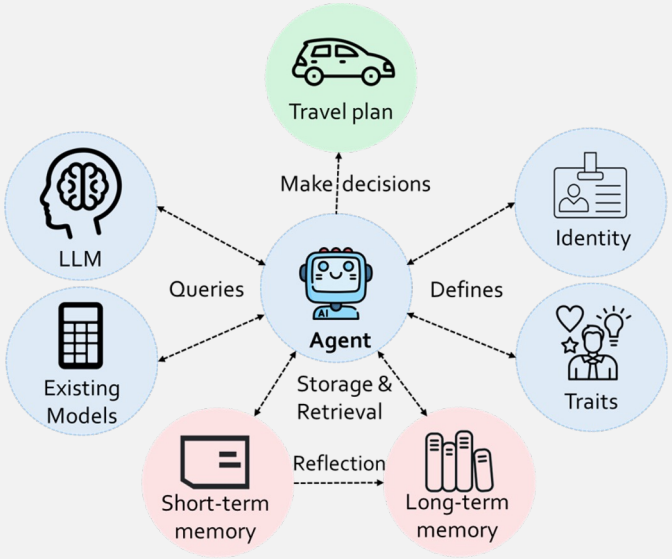
Driving ethics: bias in principles

Alignment is needed

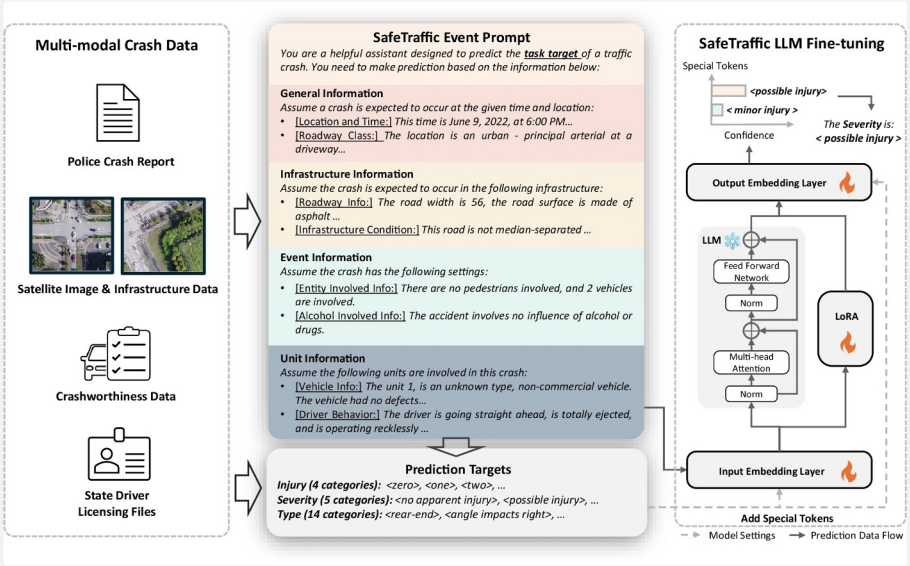


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Wang, L. et al. (2025). Comparing AI and human decision-making mechanisms in daily collaborative experiments. Iscience, 28(6).
Yan, Y. et al. (2026). Valuing time in silicon: Can large language models replicate human value of travel time. Travel Behaviour and Society, 44, 101245.

Developing Human-like LLMs and Agents



Using agents and prompt optimization to mimic human decision-making processes



Using post-training to further train LLMs to mimic human responses

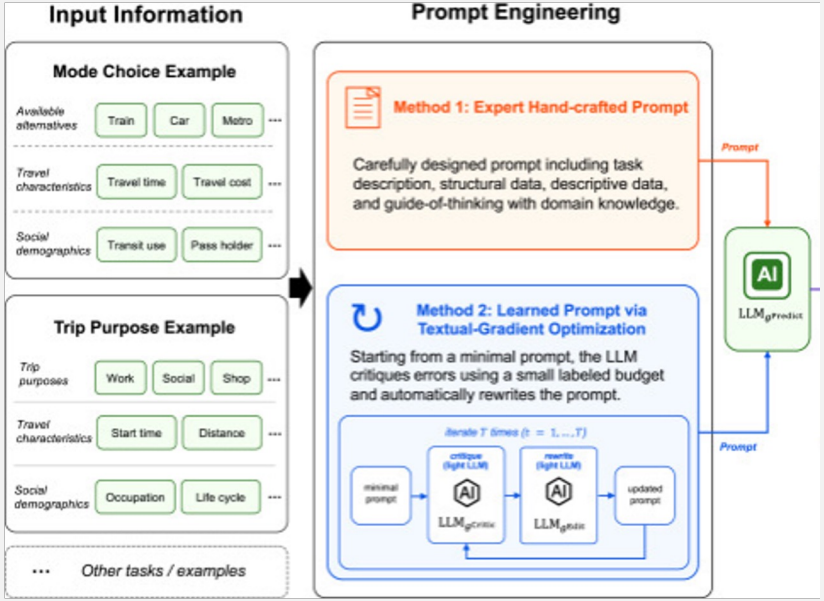
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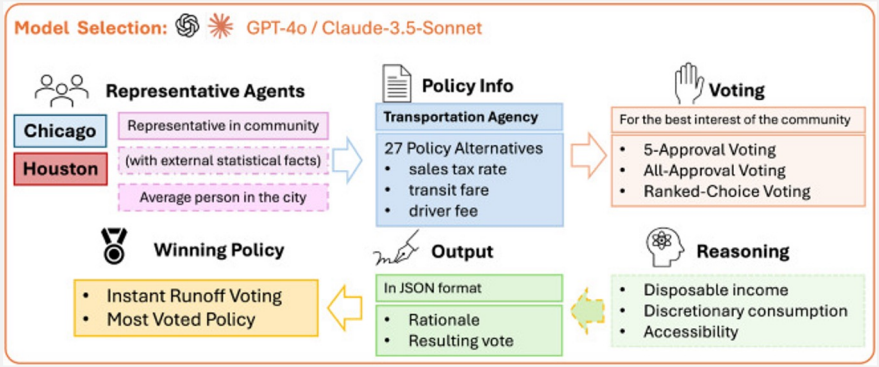
Zhao, Y, et al. (2025). SafeTraffic Copilot: adapting large language models for trustworthy traffic safety assessments and decision interventions. Nature Communications, 16(1), 8846.

Slides adapted from Tianming Liu (tianmliu@umich.edu)

Observations So Far from the Community

LLM's internal knowledge and role-playing ability can facilitate travel behavior forecasting and transportation planning





LLM agents can function as representative agents in transportation planning to reduce participation bias

LLMs can use internal knowledge to facilitate simulation of travel behavior

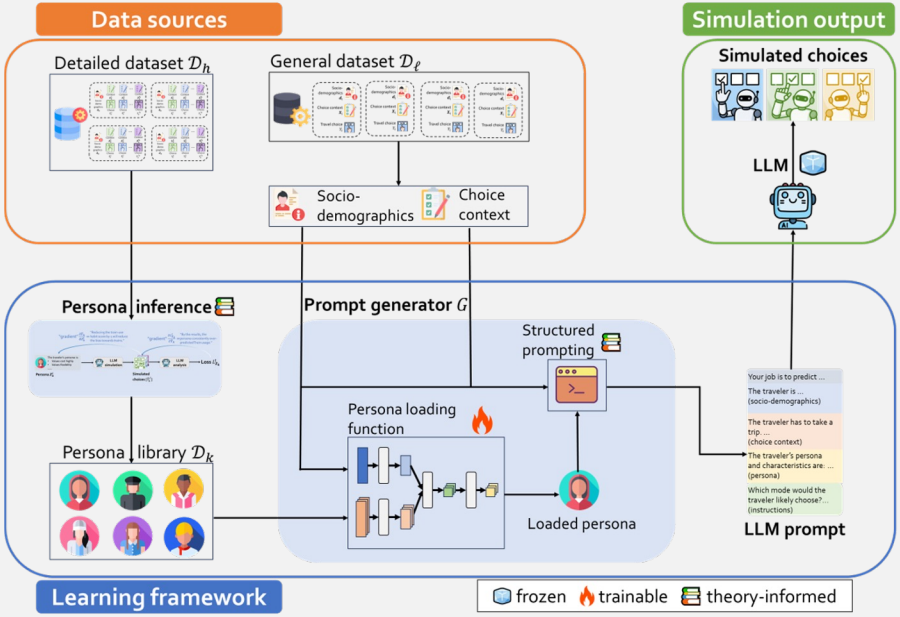
Mo.B. et al. (2026) Large language models for travel behavior prediction. Transportation Research Interdisciplinary Perspectives, 38, 102124.

Yan, X., Dai, T., & Nie, Y. M. (2026). Addressing the alignment problem in transportation policy making: an LLM approach. Transportation Research Part C: Emerging Technologies, 188, 105686.

*Cho, J. H., & **Wu, C**. (2026). AGORA: Can Deliberation and Governance Gates Absorb Participation Bias in Transit Planning?. IEEE Intelligent Transportation Systems Conference.*

Observations So Far from the Community

LLM agents can be trained with limited human data to generate better travel demand forecasts than existing models.



- LLM agents can only use a small amount of human data to simulate travel choices well
- By relaxing behavior assumptions, LLM agents can adapt to diverse traveler behaviors
- With memories, agent behavioral archetypes, and post-training with human data, LLM agents can diagnose patterns and intentions in mobility traces and generate good trajectory forecasts

Liu, T. et. al. (2026). Aligning LLM with Humans for Travel Choices: A Persona-Based Embedding Learning Approach. Transportation Science, Articles in Advance.
Liu, T. et al. (2026). Aligning LLM agents with human learning and adjustment behavior: a dual agent approach. Transportation Research Part C: Emerging Technologies, 191, 105818.
Qin, Z. et.la. (2026). A foundational individual mobility prediction model based on open-source LLMs. Transportation Research Part C: Emerging Technologies, 185, 105562.
Wang, J. et al.. (2024). Large language models as urban residents: An llm agent framework for personal mobility generation. Advances in Neural Information Processing Systems, 37, 124547-124574.

Challenges

Foundation and Use cases

- Identify the best use case and trade-offs with LLMs: where it gains the most, and when it's best to apply them
- Developing unified approaches and procedures to apply LLMs in different contexts

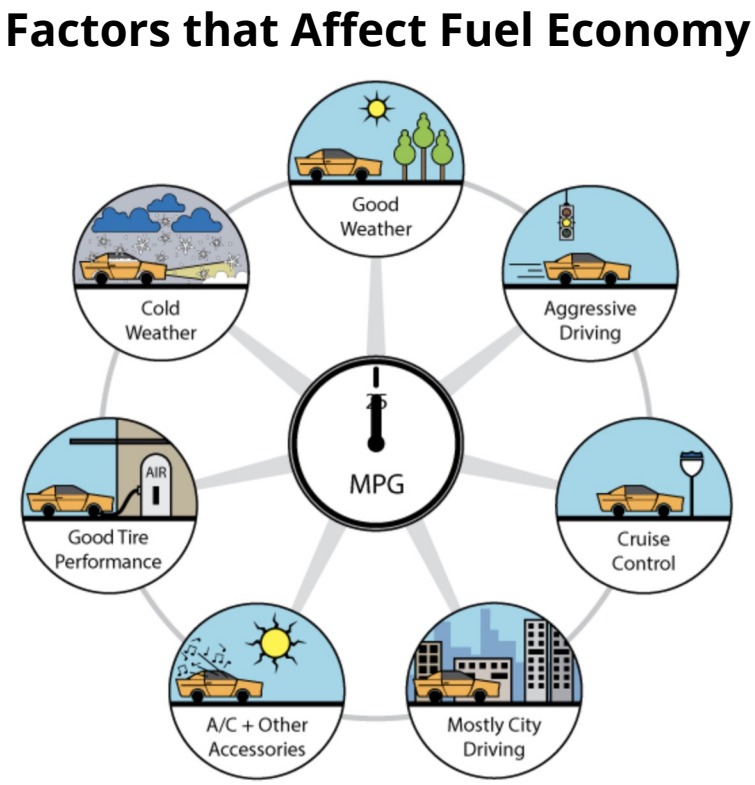
Validation

- Systematic benchmarking of LLMs' capabilities and performance
- Move beyond observed behavior to underlying value alignment

Scalability

- Reduce computational cost, energy usage and latency for large-scale applications

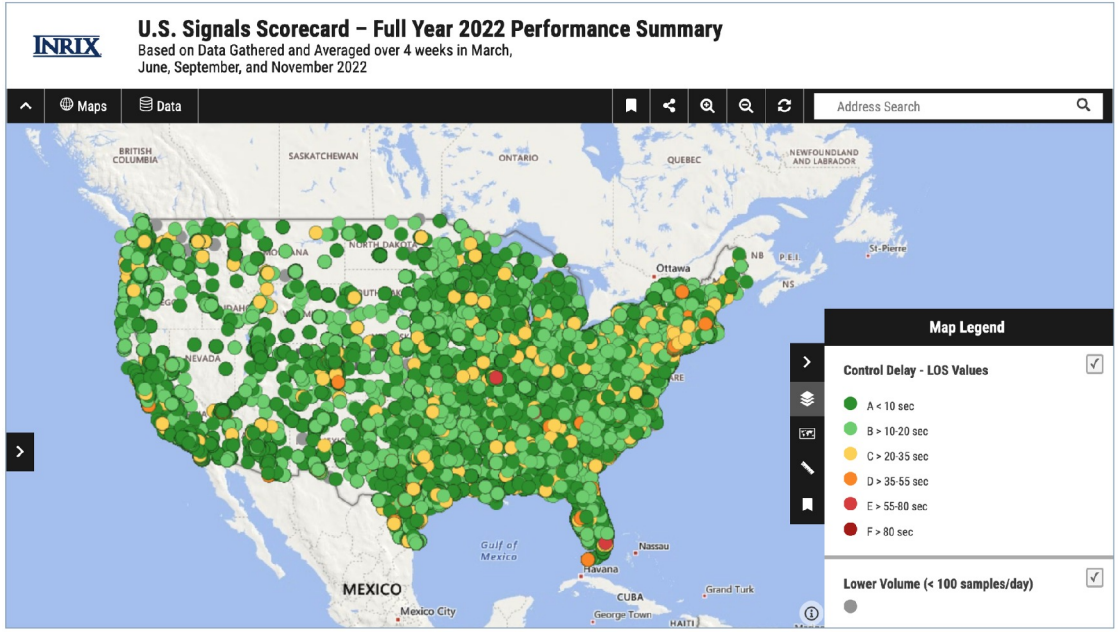
Deep Dive: Improve AI for Transport Efficiency



Source: US EPA, “Your Mileage May Vary,” 2026.

INRIX U.S. Signals Scorecard

2022 Annual Summary



Inputs

~5 Billion
Total Number of Observed Crossings Used to Generate Results

~10 Million
Number of Connected Vehicles Providing Location and Movement Data



242,757
Signalized Intersections Analyzed

All 50 States
(Plus District of Columbia)

400+ Regions

1,150+ Counties

Results

23,308
Intersection Avg Daily Traffic

18.1
Seconds of Delay Per Vehicle

63.5%
Arrival on Green

117.4
Total Hours of Daily Delay

2.53 Days
Days to Generate 1 Metric Tonne of Carbon Emissions From Delay

0.97 Days
Days to Consume 1 Barrel of Oil From Delay

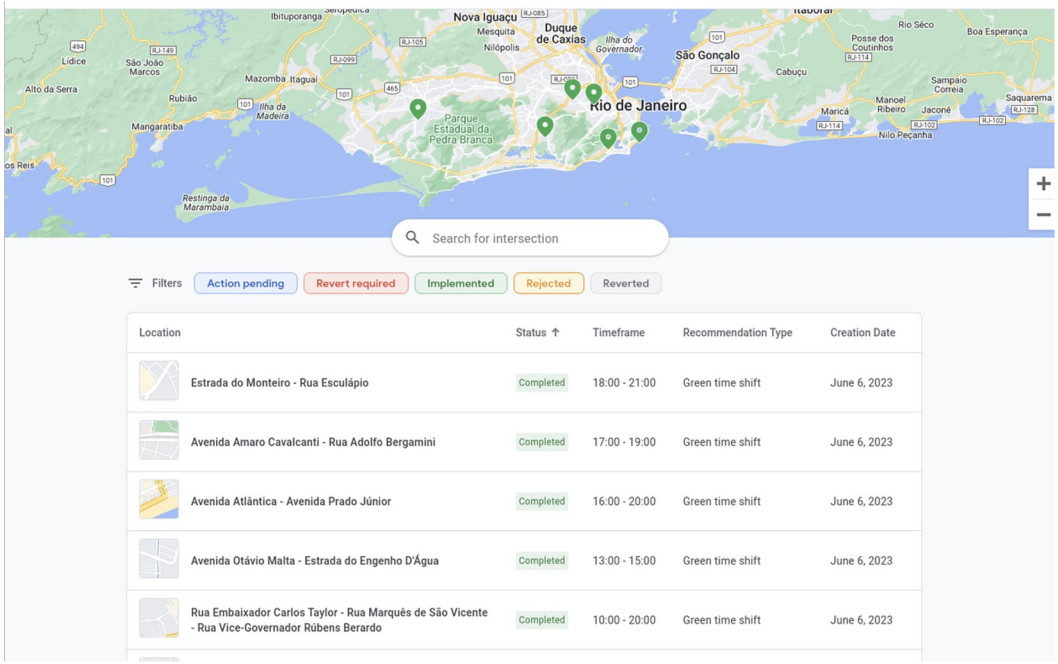
Average Traffic Signal

INRIX U.S. Signals Scorecard: 2022 Annual Summary. INRIX. https://inrix.com/signals-scorecard/.

Project Green Light (Google AI)

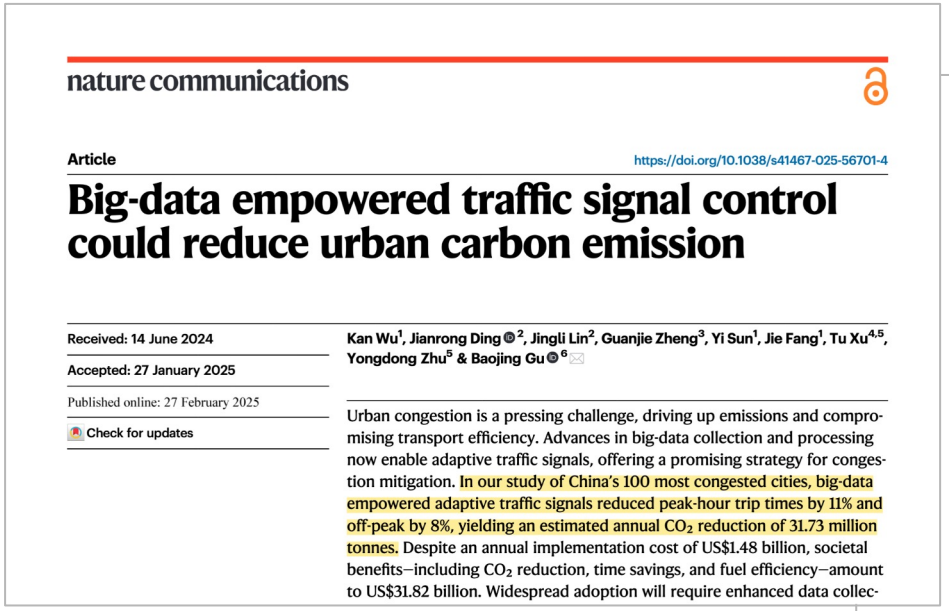
- Big data for traffic signal timing
  - Launched in 2023; live in 20 cities
  - Up to 30% reduction in stops and 10% reduction in GHG emissions*
- Uses AI to infer current pre-timed traffic light parameters
  - Cycle length
  - Transition time
  - Green split (i.e. right-of-way time and order)
  - Coordination
  - Sensor operation (actuation))
- Provides recommendations to city traffic engineers on adjustments to traffic light parameters

* No independent audit available



Google AI's Green Light. sites.research.google/gr/greenlight.

AI for traffic signal optimization



nature communications

Article

https://doi.org/10.1038/s41467-025-56701-4

Big-data empowered traffic signal control could reduce urban carbon emission

Received: 14 June 2024

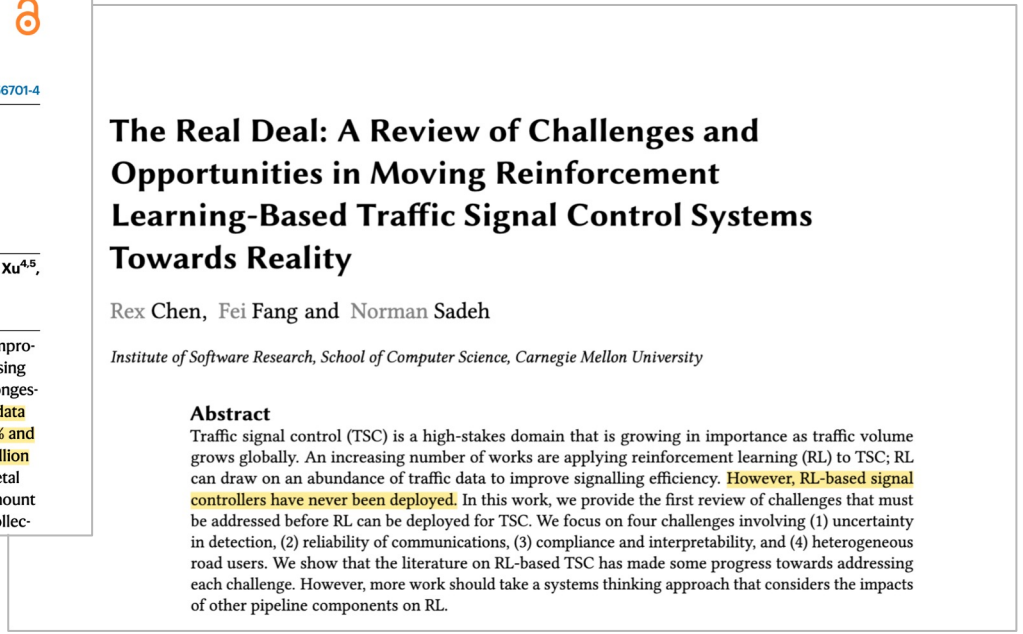
Accepted: 27 January 2025

Published online: 27 February 2025

Check for updates

Kan Wu[1], Jianrong Ding[2], Jingli Lin[2], Guanjie Zheng[3], Yi Sun[1], Jie Fang[1], Tu Xu[4,5], Yongdong Zhu[5] & Baojing Gu[6]

Urban congestion is a pressing challenge, driving up emissions and compromising transport efficiency. Advances in big-data collection and processing now enable adaptive traffic signals, offering a promising strategy for congestion mitigation. In our study of China's 100 most congested cities, big-data empowered adaptive traffic signals reduced peak-hour trip times by 11% and off-peak by 8%, yielding an estimated annual CO_2 reduction of 31.73 million tonnes. Despite an annual implementation cost of US$1.48 billion, societal benefits—including CO_2 reduction, time savings, and fuel efficiency—amount to US$31.82 billion. Widespread adoption will require enhanced data collec-



The Real Deal: A Review of Challenges and Opportunities in Moving Reinforcement Learning-Based Traffic Signal Control Systems Towards Reality

Rex Chen, Fei Fang and Norman Sadeh

Institute of Software Research, School of Computer Science, Carnegie Mellon University

Abstract

Traffic signal control (TSC) is a high-stakes domain that is growing in importance as traffic volume grows globally. An increasing number of works are applying reinforcement learning (RL) to TSC; RL can draw on an abundance of traffic data to improve signalling efficiency. However, RL-based signal controllers have never been deployed. In this work, we provide the first review of challenges that must be addressed before RL can be deployed for TSC. We focus on four challenges involving (1) uncertainty in detection, (2) reliability of communications, (3) compliance and interpretability, and (4) heterogeneous road users. We show that the literature on RL-based TSC has made some progress towards addressing each challenge. However, more work should take a systems thinking approach that considers the impacts of other pipeline components on RL.

[1] K. Wu et al., "Big-data empowered traffic signal control could reduce urban carbon emission," Nat Commun, 2025, doi: 10.1038/s41467-025-56701-4.
[2] R. Chen, F. Fang, and N. Sadeh, "The real deal: A review of challenges and opportunities in moving reinforcement learning-based traffic signal control systems towards reality," arXiv preprint arXiv:2206.11996, 2022.

Energy Policy 38 (2010) 762–769

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Eco-driving: An overlooked climate change initiative

Jack N. Barkenbus

Climate Change Research Network, Vanderbilt University, 131 21st Avenue South, Nashville, TN 37203, United States

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Mitigation

ABSTRACT

The actions individuals can take to mitigate climate change are, in the aggregate, significant. Mobilizing individuals to respond personally to climate change, therefore, must be a complementary approach to a nation's climate change strategy. One action item overlooked in the United States has been changing driver behavior or style such that eco-driving becomes the norm rather than the exception. Evidence to date indicates that eco-driving can reduce fuel consumption by 10%, on average and over time, thereby reducing CO_2 emissions from driving by an equivalent percentage. A sophisticated, multi-dimensional campaign, going well beyond what has been attempted thus far, will be required to achieve such savings on a large scale, however, involving education (especially involving the use of feedback devices), regulation, fiscal incentives, and social norm reinforcement.

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[1] J. N. Barkenbus, "Eco-driving: An overlooked climate change initiative," Energy Policy, 2010, doi: 10.1016/j.enpol.2009.10.021.

Eco-driving for the Planet (using AI)

Mitigating Metropolitan Carbon Emissions with Dynamic Eco-driving at Scale

Transportation Research Part C: Emerging Technologies 2025


Vindula Jayawardana


Baptiste Freydt


Ao Qu


Cameron Hickert


Edgar Sanchez


Catherine Tang


Mark Taylor


Blaine Leonard


Cathy Wu

Policy Implications of Connected and Automated Vehicles?

CAV affordance: Eco-driving at signalized intersections

Video credits: Audi



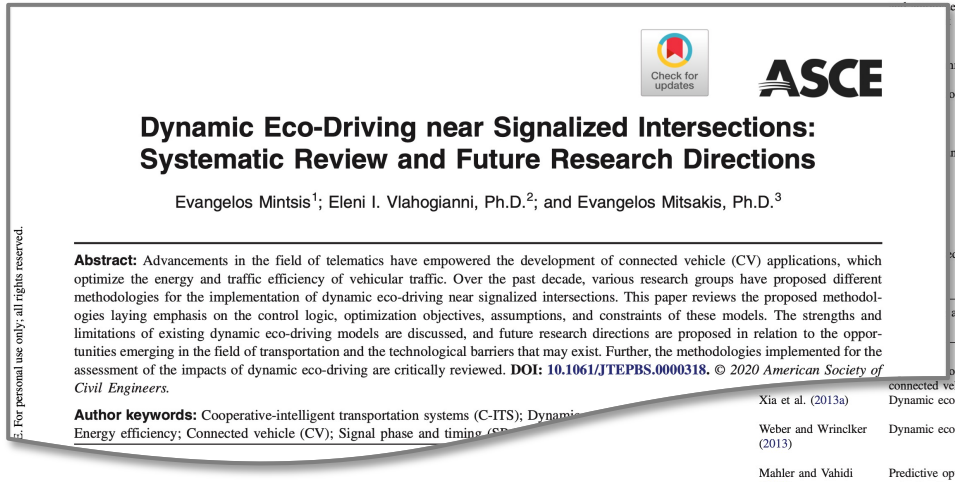
From 'how to eco-drive' (1000+ articles) to 'should we eco-drive' (≈0 articles)?

Research Question: Would intelligent control of vehicles to reduce CO_2 emissions at intersections at the city scale move the needle on climate change mitigation goals?

* Estimated using Google Scholar

[1] Mintsis et al. *Dynamic eco-driving near signalized intersections: Systematic review and future research directions*. Journal of Transportation Engineering, Part A, 2020

Eco-driving savings



Check for updates

ASCE

Dynamic Eco-Driving near Signalized Intersections: Systematic Review and Future Research Directions

Evangelos Mintsis[1]; Eleni I. Vlahogianni, Ph.D.[2]; and Evangelos Mitsakis, Ph.D.[3]

Abstract: Advancements in the field of telematics have empowered the development of connected vehicle (CV) applications, which optimize the energy and traffic efficiency of vehicular traffic. Over the past decade, various research groups have proposed different methodologies for the implementation of dynamic eco-driving near signalized intersections. This paper reviews the proposed methodologies laying emphasis on the control logic, optimization objectives, assumptions, and constraints of these models. The strengths and limitations of existing dynamic eco-driving models are discussed, and future research directions are proposed in relation to the opportunities emerging in the field of transportation and the technological barriers that may exist. Further, the methodologies implemented for the assessment of the impacts of dynamic eco-driving are critically reviewed. **DOI:** 10.1061/JTEPBS.0000318. © *2020 American Society of Civil Engineers.*

Author keywords: Cooperative-intelligent transportation systems (C-ITS); Dynami… Energy efficiency; Connected vehicle (CV); Signal phase and timing (SP…

…: For personal use only; all rights reserved.

- Estimated energy / emissions savings range from **2-56%** (25 studies)

Energy / emissions savings

Table 3. Evaluation methodologies of existing dynamic eco-driving models and corresponding impacts

Author(s)	Speed advisory model name	Evaluation methodology	Test network configuration	Vehicle type	Energy savings (%)	Emissions savings (%)	Travel time savings (%)	Real-time ready
Hao et al. (2018)	EAD	Field experiment (real-world traffic)	El Camino Real test site	Single-vehicle (2.5L 4-cylinder)	2 (all trips)	7 (CO) 18 (HC) 13 (NO_x)	—	—
Jiang et al. (2017)	Dynamic eco-driving under partially connected …ed vehicles	Simulation (Excel VBA, MATLAB, and VISSIM)	Hypothetical intersection	—	2.02	1.97	10.80	Yes
		Field experiment (real-world traffic)	DRIVE C2X test site (Gothenburg, Sweden)	10 retrofitted prototype vehicles	—	—	—	Yes
	…mendation	Field experiment	Virginia Smart Road Test facility	2014 Cadillac SRX	19	—	10	Yes
	…o-driving	Field experiment (real-world traffic)	Signalized arterial corridor (Thessaloniki, Greece)	340 taxis	—	9 (compliant versus noncompliant)	—	Yes
		MATLAB	—	30 top sold vehicles in the US	—	—	—	Yes
	…nce model	Simulation (EstiNet)	3.7 km urban arterial road in Beijing	—	—	2.13	8.15	—
		Numerical evaluation	Hypothetical intersection	—	3–12	5–20 (CO) 3–14 (HC) 6–21 (NO_x)	—	Yes
		Controlled experiment	Palmyrita Avenue, Riverside, California	2008 Nissan Altima	5–27	—	—	Yes
	…d dynamic	Simulation (INTEGRATION)	Cross intersection (Blacksburg, Virginia)	—	13	13 (CO, HC, CO_2, and NO_x)	38	—
	—	Simulation MATLAB (GPOPS)	—	—	—	—	—	—
	…assistant	Field experiment (real-world traffic)	Urban network	5 different vehicles (series-production)	29	—	–9	Yes
	—	MATLAB (sensitivity analysis)	—	—	4.9	—	—	Yes
	…o-driving for connected vehicles	Simulation (PARAMICS)	Hypothetical intersection	Single and multivehicle	—	50 (NO_x)	14	—
Xia et al. (2013a)	Dynamic eco-driving	Simulation (PARAMICS)	11-signalized arterial corridor	Single and multivehicle	31	—	—	Yes
Weber and Wrinclker (2013)	Dynamic eco-driving	Field experiment	Richmond Field Station test track	BMW mid-sized sedan	12.5	13 (CO_2)	0.7	Yes
Mahler and Vahidi (2012)	Predictive optimal velocity planning algorithm	MATLAB Field experiment	El Camino Real test site (Greenville, South Carolina)	—	14	—	—	Yes
Rakha et al. (2012)	—	MATLAB	—	—	—	—	—	Yes
Schuricht et al. (2011)	Predictive driver assistance	Simulation (IDM)	—	—	—	—	—	—
Raubitschek et al. (2011)	Predictive driving strategy	MATLAB Field experiment	— BMW test track (Aschheim, Munich, Germany)	—	30	—	—	—
Barth et al. (2011)	Dynamic eco-driving	Simulation (PARAMICS)	Hypothetical 10-signalized arterial	Mid-sized Sedan	8.7	—	—	—
Asadi and Vahidi (2011)	PCC	SIMULINK (MATLAB)	Urban road Suburban road	—	10	—	—	Yes
Tielert et al. (2010)	Speed adaptation model	Simulation (VISSIM)	Single-lane road segment Karlsruhe's inner city, Germany	EURO4 Otto and diesel engines	12	56 (CO_2)	—	Yes
Vreeswijk et al. (2010)	—	Simulation (VISSIM)	Four-leg intersection (Rotterdam, Netherlands)	—	47	56 (CO_2)	—	—
Saust et al. (2010)	—	Field experiment	Ring road of Braunschweig, Germany (two-lane arterial road)	—	22 8	80 (CO); 35 (NO_x); 18 (PM) —	—	—
Mandava et al. (2009)	Arterial velocity planning algorithm	Stochastic simulation	Hypothetical 10-signalized arterial	LDV24 and LDV17	35	—	—	Yes
Li et al. (2009)	ADAS	Parametric analysis Simulation	—	—	12–14	12–14 (CO_2)	—	—
					14 8	—	—	—

Mintsis et al. *Dynamic eco-driving near signalized intersections: Systematic review and future research directions*. Journal of Transportation Engineering, Part A, 2020

Impact calculation (back of the envelope*)

Driving impact

51.9%
x [6, 28]%

[3.1, 14.5]%

Vehicle miles traveled (VMT) near **signalized intersections** [1]

Avoidable emissions from **eco-driving** (±1 std from [2])

of CO_2 emissions from driving is simply "wasted" at intersections

National impact

x 29%
x 81%

[0.7, 3.41]%

GHG from **transportation** sector [3]

↳ GHG from **on-road vehicles** [4]

of U.S. CO_2 emissions is simply "wasted" at intersections

Gold standard:
–1% global GHG
Breakthrough Energy Ventures
Led by Bill Gates

[1] U.S. Federal Highway Administration (FHWA). *Highway Statistics* 2021. 2023.
[2] Mintsis et al. *Dynamic eco-driving near signalized intersections: Systematic review and future research directions*. Journal of Transportation Engineering, Part A, 2020.
[3] U.S. Environmental Protection Agency, *Inventory of U.S. greenhouse gas emissions and sinks*. 2023.
[4] U.S. Environmental Protection Agency, *Fast Facts on Transportation Greenhouse Gas Emissions*. 2023.

* Calculations based on statistics from the United States.

Regional Eco-driving Problem

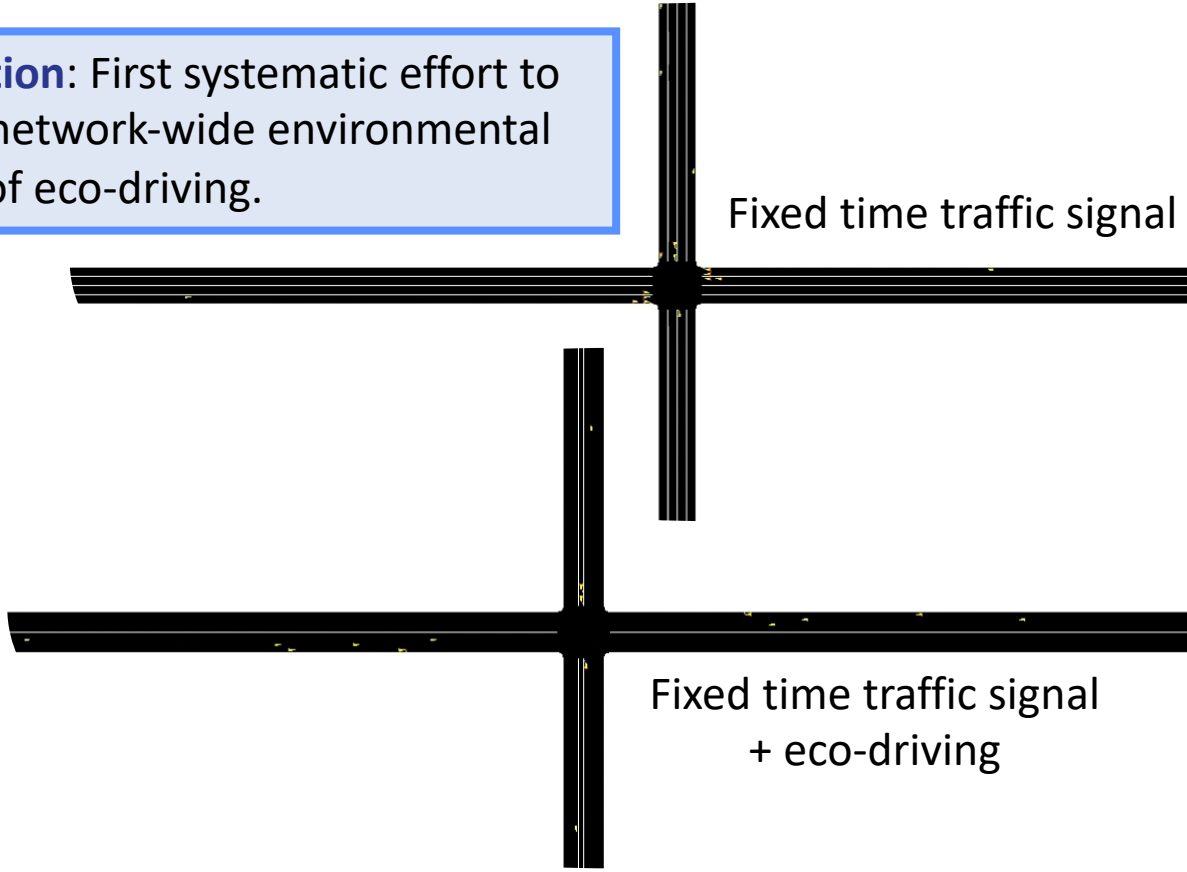


San Francisco

Contribution: First systematic effort to quantify network-wide environmental benefits of eco-driving.

Objective: Expected fleet emissions reduction without significant impact on travel time and intersection throughput

Subject to: safety requirements, vehicle actuator limits, and road rules



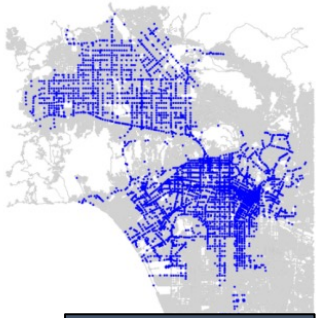
All scenarios are modeled in industry-grade simulators

6,011 data-informed intersection environments are modeled in the industry-grade SUMO microscopic simulator

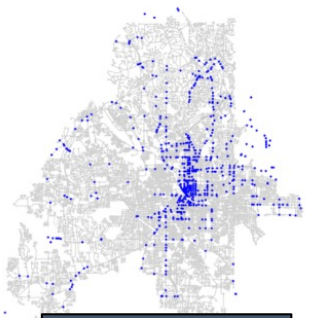
1M+ Traffic Scenarios



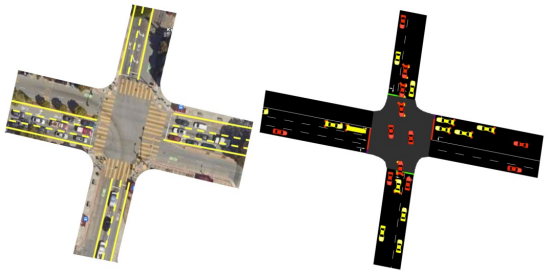
San Francisco



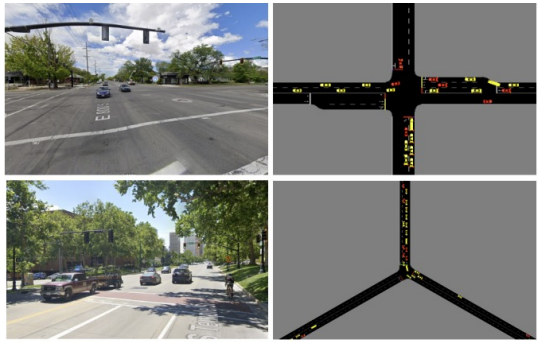
Los Angeles



Atlanta







Real-world intersection vs simulation

Qu, Valiveru, Tang, Jayawardana, Freydt, Wu, *What is a typical signalized intersection in a city? A pipeline for intersection data imputation from OpenStreetMap*, Transportation Research Board, 2023.
Jayawardana et al. *IntersectionZoo: Eco-driving for benchmarking contextual reinforcement learning*. International Conference on Learning Representations (ICLR), 2025.

All scenarios are modeled using open data and tools

OpenStreetMap

NOAA

PRECISION TRAFFIC & SAFETY SYSTEMS

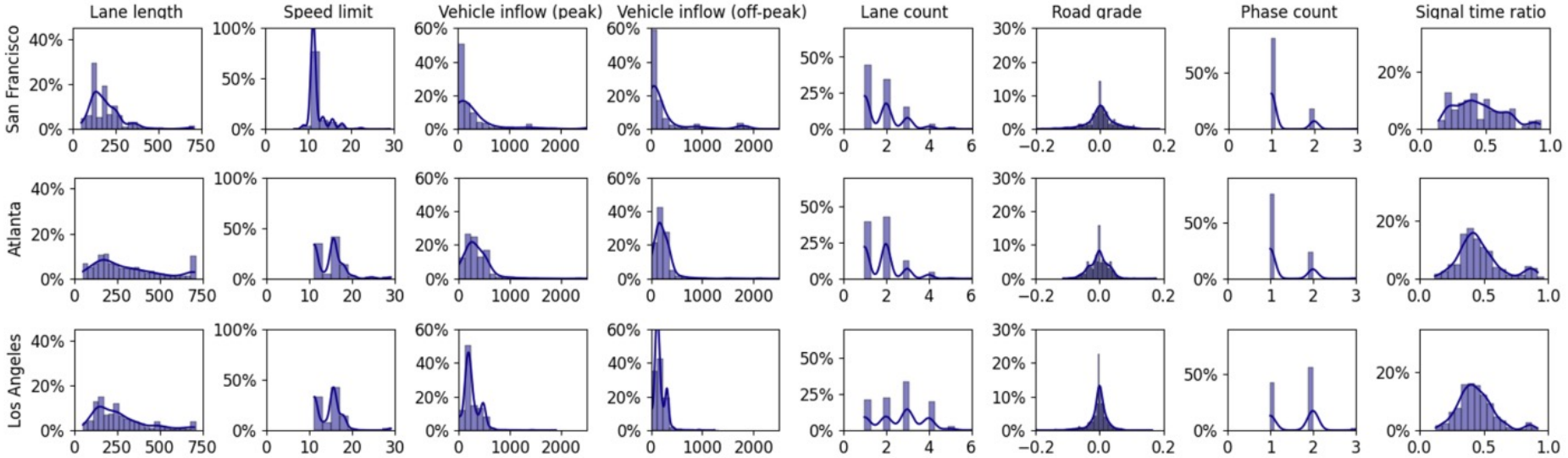
SFMTA

GDOT Georgia Department of Transportation

CA.GOV CALIFORNIA OPEN DATA PORTAL

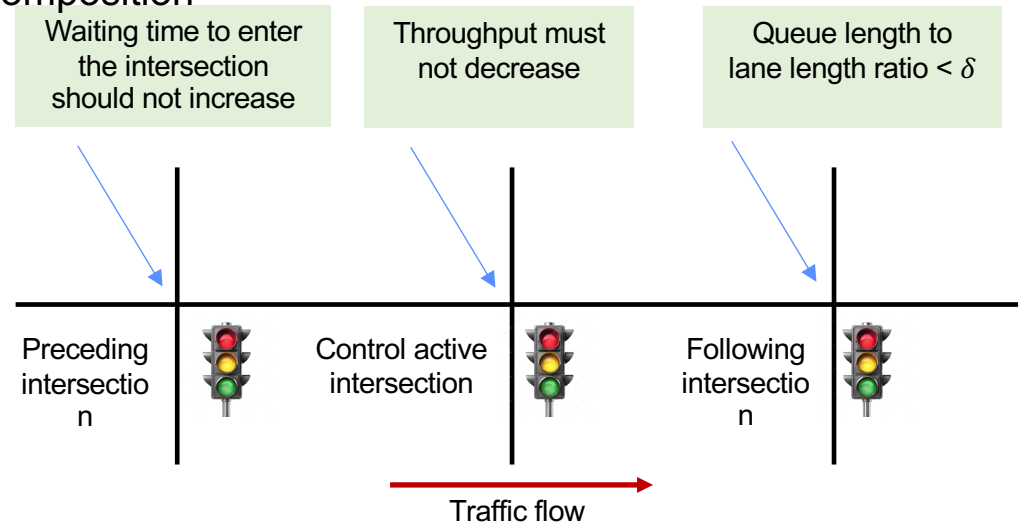
US Geological Survey

MOVES Motor Vehicle Emission Simulator



Network decomposition

Requirements for network decomposition



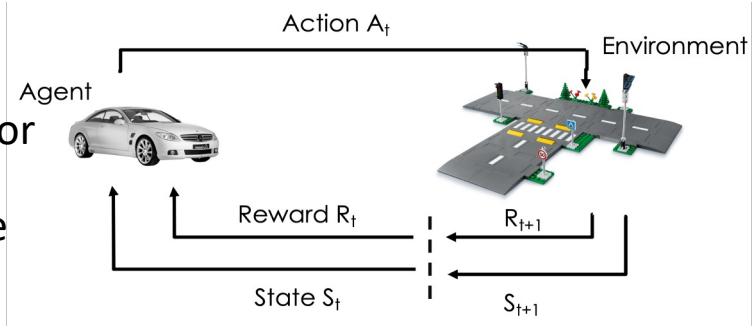
When any of these requirements are violated with eco-driving, the benefits are defaulted to zero

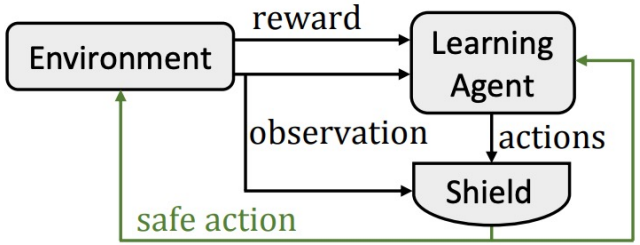
This makes the benefit levels a lower bound of the possible benefits

Modeling the Eco-driving Scenario as an MDP

- **Training protocol**: Shared parameter multi-agent RL, following centralized training and decentralized execution.
  - Decentralized Partially Observed Markov Decision Process (Dec-POMDP)

- For each eco-driving vehicle:
  - **Observation**: Vehicle sensing, nearby vehicle sensing, traffic signal timing info, and context for the intersection
  - **Action**: Longitudinal acceleration of the vehicle
  - **Reward**: A linear combination velocity, emissions, and idling
  - **Transition function**:
    - Behavior of all other road users, traffic signal
    - Hard constraints are satisfied with post-shielding
  - **Horizon**: 12.5 min (1500 steps at 0.5 sec / step) with discount factor $\gamma = 0.99$
    - Typical traffic signal cycle is 1-3 min



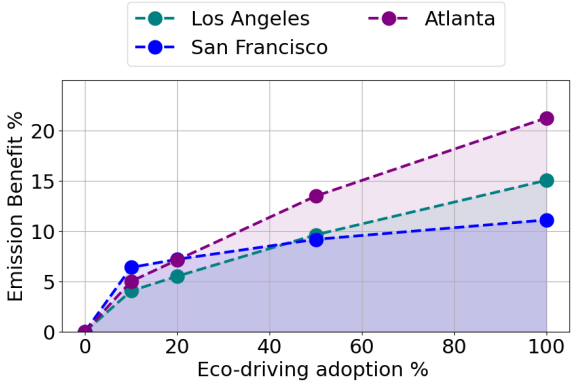


Results: Overall Effectiveness

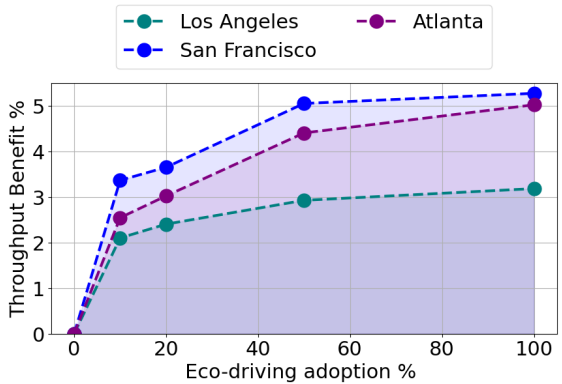
Gold standard:
–1% global GHG
Breakthrough Energy Ventures
Led by Bill Gates

Eco-driving could cut city-wide intersection CO_2 emissions by **11-21%**.
This translates to **1.34%-2.68%** U.S. CO_2 emissions.

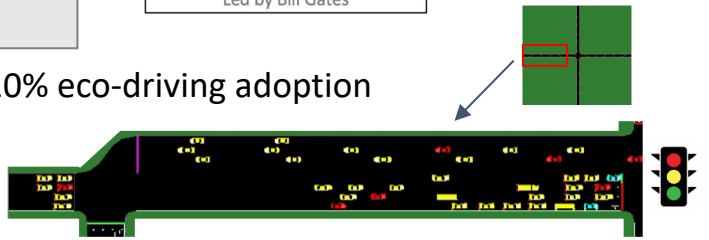
Emission reduction



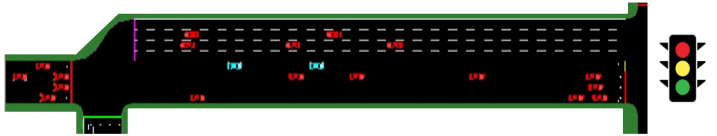
Throughput increase

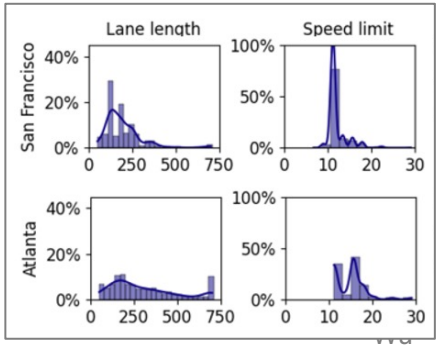


20% eco-driving adoption



100% eco-driving adoption





- Non-linear scaling: 25%-50% of benefits from 10% eco-driving adoption

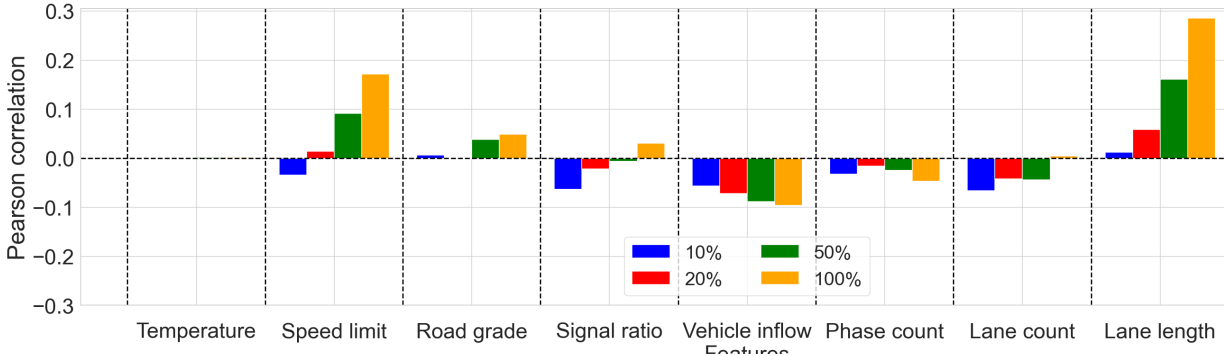
Why does Atlanta benefit more from eco-driving than SF?

Atlanta vs San Francisco

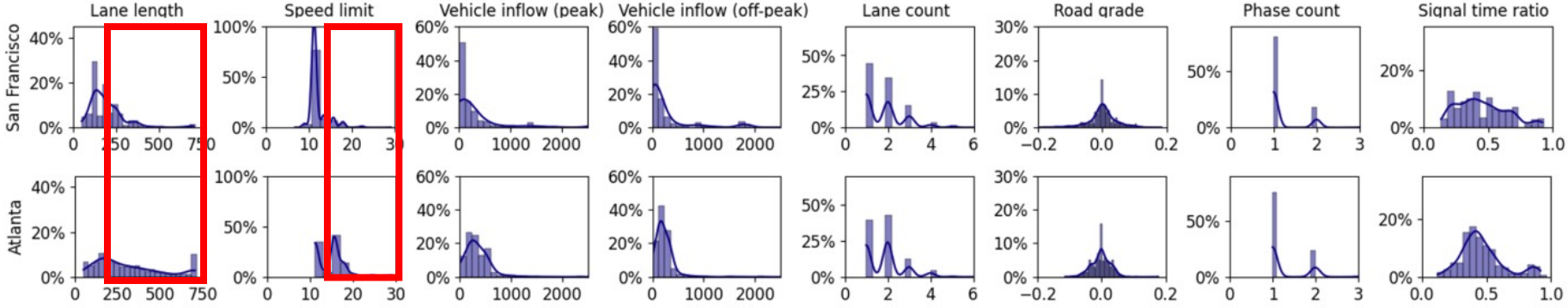
- Longer lane lengths
- Higher speed limits

These are the **two highest correlating factors** to eco-driving benefit

Pearson Correlation Analysis of Eco-driving Benefits vs Factors



City Feature Distributions



V. Jayawardana, *et al.*, ***C. Wu***, "Mitigating Metropolitan Carbon Emissions with Dynamic Eco-driving at Scale," *Transportation Research Part C: Emerging Technologies*, 2025.

Overall Eco-driving Impact calculation

Website

Driving impact

51.9%
x [11, 22]%

[5.7, 11.4]%

Vehicle miles traveled (VMT) near **signalized intersections** [1]

Avoidable emissions from **eco-driving**

of CO_2 emissions from driving is simply "wasted" at intersections

National impact

x 29%
x 81%

[1.3-2.7]%

GHG from **transportation** sector [3]

↳ GHG from **on-road vehicles** [4]

of U.S. CO_2 emissions is simply "wasted" at intersections

Gold standard:
–1% global GHG
Breakthrough Energy Ventures
Led by Bill Gates

[1] U.S. Federal Highway Administration (FHWA). *Highway Statistics* 2021. 2023.
[2] Mintsis et al. *Dynamic eco-driving near signalized intersections: Systematic review and future research directions*. Journal of Transportation Engineering, Part A, 2020.
[3] U.S. Environmental Protection Agency, *Inventory of U.S. greenhouse gas emissions and sinks*. 2023.
[4] U.S. Environmental Protection Agency, *Fast Facts on Transportation Greenhouse Gas Emissions*. 2023.

* Calculations based on statistics from the United States.

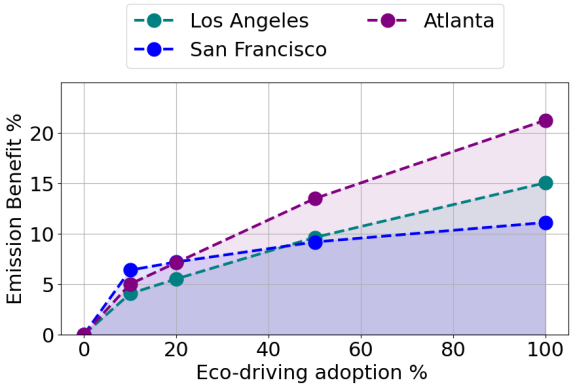
Findings and Policy Implications

Emissions impact: 11-22% of intersection CO_2 emissions

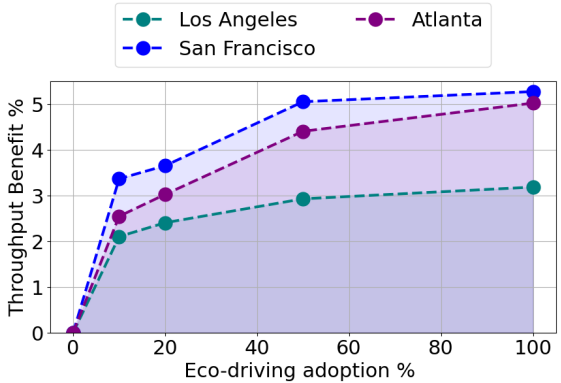
Near-term potential: Majority of impact results from a minority of drivers and intersections

Long-term relevance: Impact is robust through 2050 due to fleet impacts & travel demand

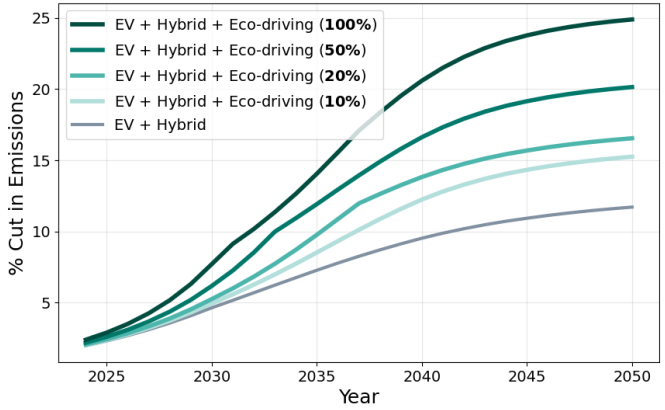
Emission reduction



Throughput increase



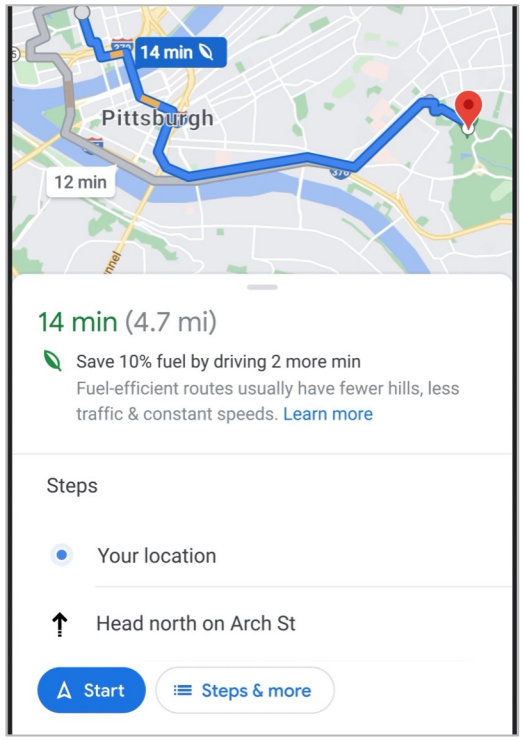
Projection through 2050 (LA)



High-impact, relatively **low cost**, and **complements** existing climate interventions

V. Jayawardana *et al.*, "Mitigating Metropolitan Carbon Emissions with Dynamic Eco-driving at Scale," *Transportation Research Part C: Emerging Technologies*, Apr. 2025.

Google Maps Eco-Friendly Routing



Step 1

Simulate vehicle fuel efficiency across vehicle powertrains

NREL's **FASTSim** technology simulates fuel efficiency across various vehicle types and powertrains, incorporating second-by-second real-world driving data to calculate real-world fuel consumption over different road types and conditions with high accuracy.

Step 2

Predict fuel consumption across unique routes

NREL's **RouteE** is then trained by the FASTSim-calculated fuel consumption over different driving conditions to predict expected fuel consumption differences among a set of defined routes.

Step 3

Integrate Google's ML Routing Algorithm

Google integrates the insights and modeling from FASTSim and RouteE across all of Google Maps, incorporating Google's predicted traffic speeds with NREL's fuel consumption modeling to predict fuel consumption for all routes in the U.S., enabling a highly accurate model to maximize fuel efficiency.

Step 4

Set parameters to optimize journey time

Finally, we developed a set of parameters and time caps to determine the optimal time vs. fuel usage trade-off within Google Maps to avoid increasing travel time for negligible fuel savings. In this way, the vast majority of our recommended routes continue to be as fast as before.

[1] Google Research, "Google Maps Eco Friendly Routing," 2021.

UPS's ORION: On-Road Integrated Optimization and Navigation

- Launched in 2013
- Chooses efficient driver routes given real-time information (traffic, weather, pickup times)
- Estimated to reduce the fuel consumption annually by 10 million gallons, and CO_2 production by 100,000 metric tons (Informs)
- Use of AI
  - Predict route performance
  - Recommends specific driver routes
- AI is promising for freight efficiency where it improves *repeated operational decisions*: routing, consolidation, load matching, empty-mile reduction, fleet scheduling, and disruption response

AI for tackling the long tail of transportation optimization

Motivating example: Vehicle Routing Problems (VRP)

One of the most widely studied in Combinatorial Optimization:

- ≈10,000 works published in 2025 alone (Google Scholar), mostly heuristics
- Direct application in real systems that distribute goods and provide services
- Last-mile delivery, waste collection, field service, ride-pooling, on-demand transit



~10,000

papers in 2025

$11T+

global logistics costs, 2023

65M+

US parcel deliveries / day

Dantzig, G. B., & Ramser, J. H. "The Truck Dispatching Problem." Management Science, 1959.
Stats: Statista/Research & Markets (2024); ShipMatrix US parcel report (2024).

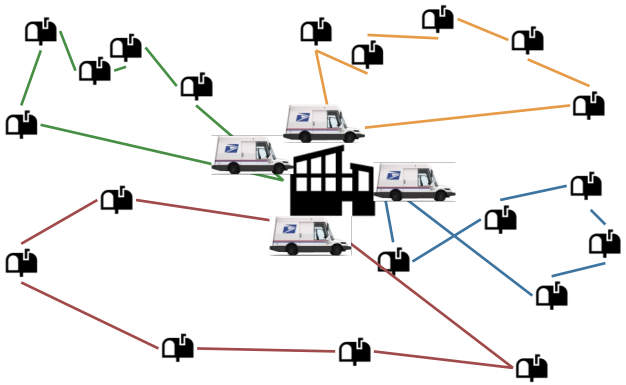
Long Tail of Transportation Optimization Problems

Definition: **Vehicle Routing Problems (VRPs)**

Given

- Depot
- N customers (location, demand)
- Vehicle fleet (capacity)
- … **Other constraints** …

Find the lowest cost set of routes that satisfies all customers



Classical dimensions

- Vehicle capacities
- Time windows
- Heterogeneous fleets
- Multiple depots
- Pickup and delivery, backhauling
- Split delivery
- Arc routing (e.g., garbage collection)

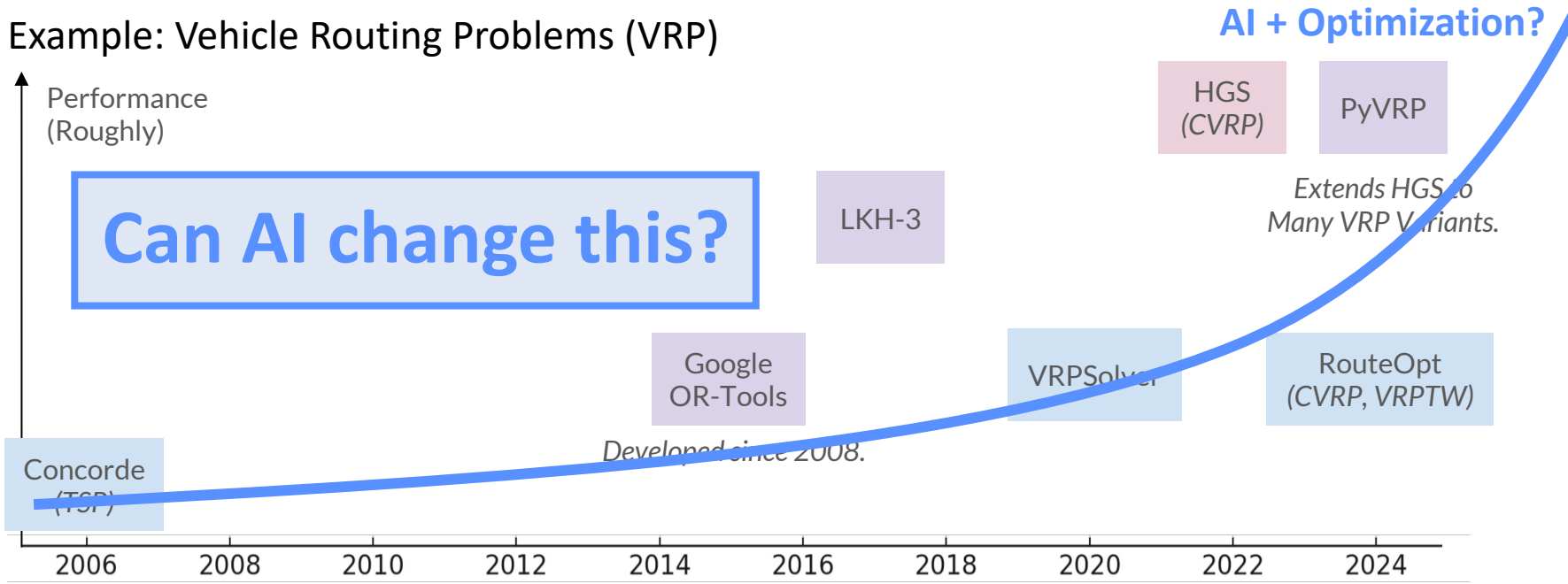
Emerging variants

- Electric vehicle routing (charging decisions)
- Drone routing (3D, endurance limits)
- Warehouse routing (pickers, sortation)
- Multi-modal logistics (truck + drone, rail + truck)

Laporte, G. "Fifty Years of Vehicle Routing," Transportation Science, 2009.
Dantzig, G. B., & Ramser, J. H. "The Truck Dispatching Problem." Management Science, 1959.

Solving the Long Tail is Slow and Laborious

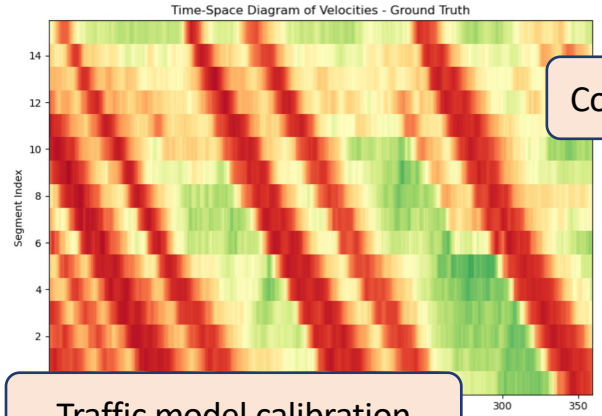
Example: Vehicle Routing Problems (VRP)



*Roughly, the y axis corresponds to the performance of the solver (e.g. HGS > LKH-3 > OR-Tools).

Laporte, G. “Fifty Years of Vehicle Routing.” Transportation Science, 2009.
Dantzig, G. B., & Ramser, J. H. “The Truck Dispatching Problem.” Management Science, 1959.

The Long Tail of Optimization is Cross-Cutting



Traffic model calibration

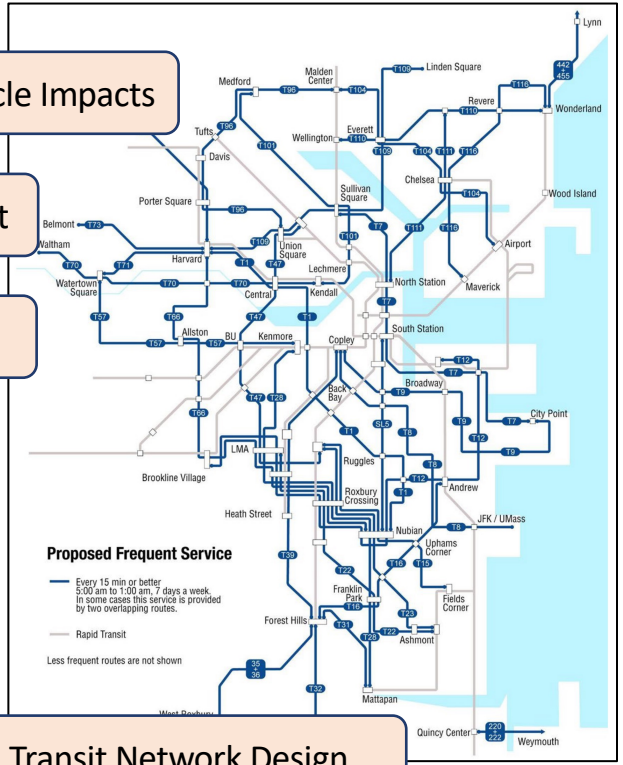
Connected and Automated Vehicle Impacts

Dynamic traffic assignment

Network optimization



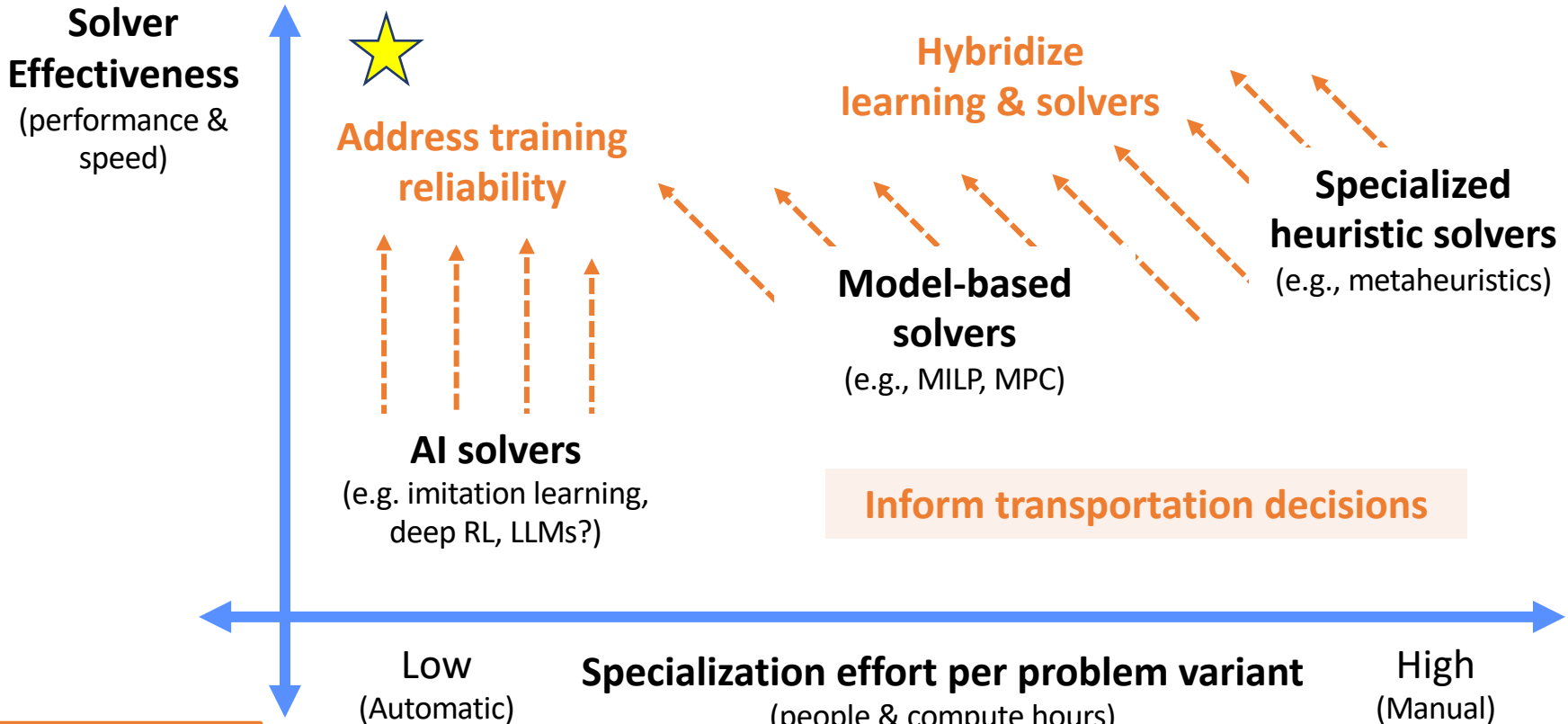
Warehouse operations



Transit Network Design

Wu

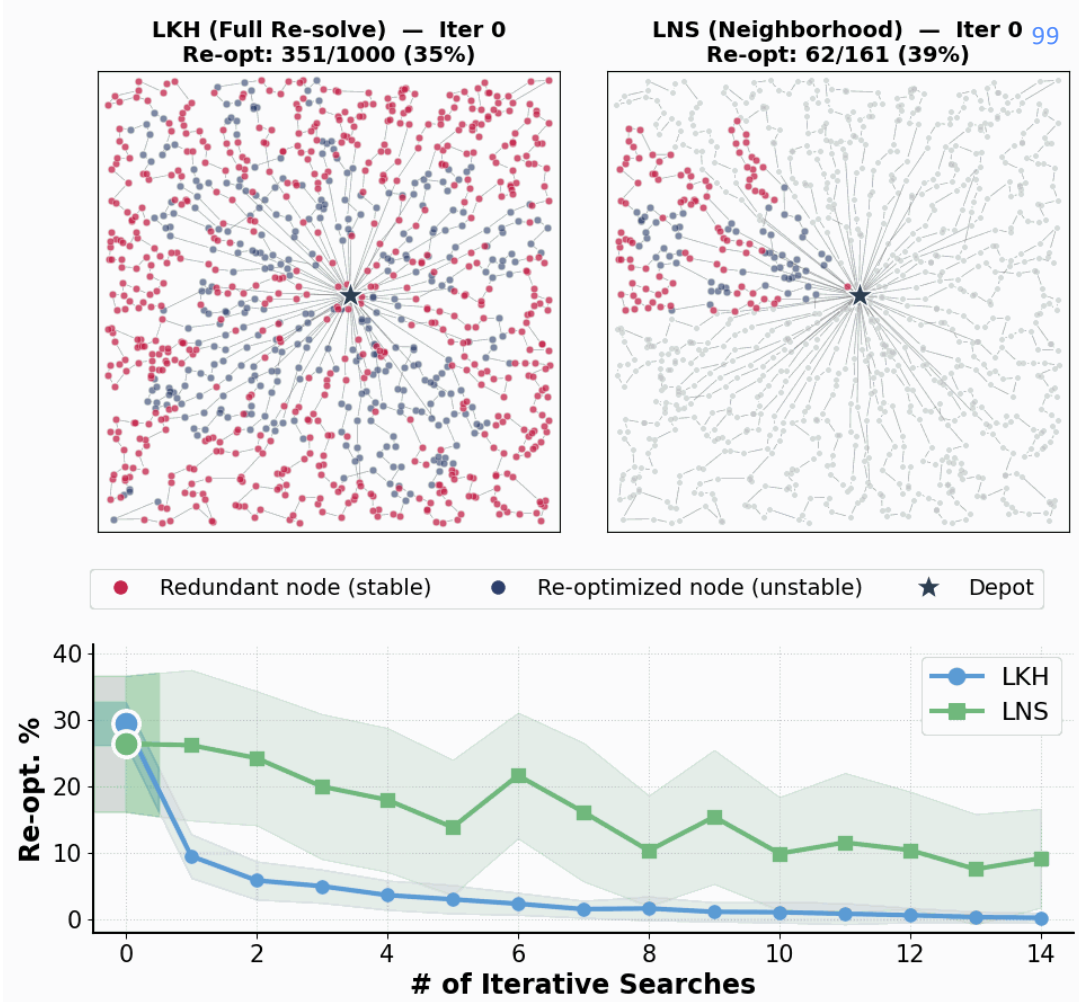
Optimization Solver Landscape



My research lab

Solver Redundancy

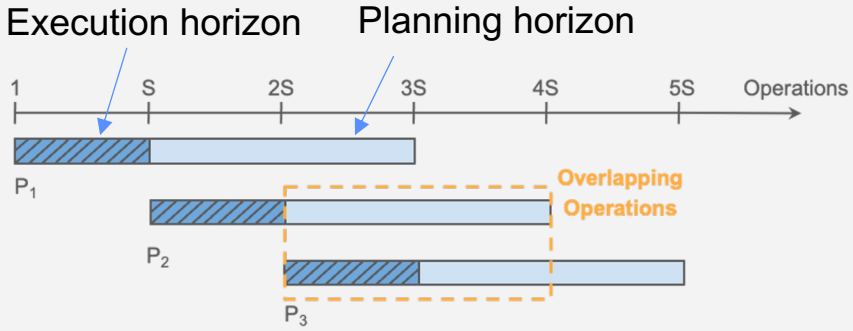
- Example: Vehicle Routing (Solvers: LKH, LNS + LKH)



W. Ouyang, S. Li, Y. Ma, and C. Wu, "Learning to Segment for Vehicle Routing Problems," International Conference on Learning Representations (ICLR), 2026. **Oral (1%)**.

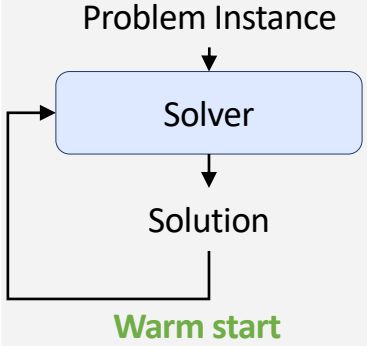
Learn to Reuse: Avoid Redundant Calculations

Setting: Rolling Horizon Optimization (RHO)

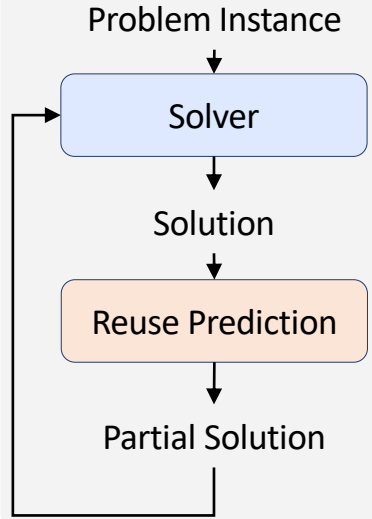


L-RHO: Up to 50% faster by *learning to reuse solutions in consecutive RHO subproblems* [1]

Warm start RHO



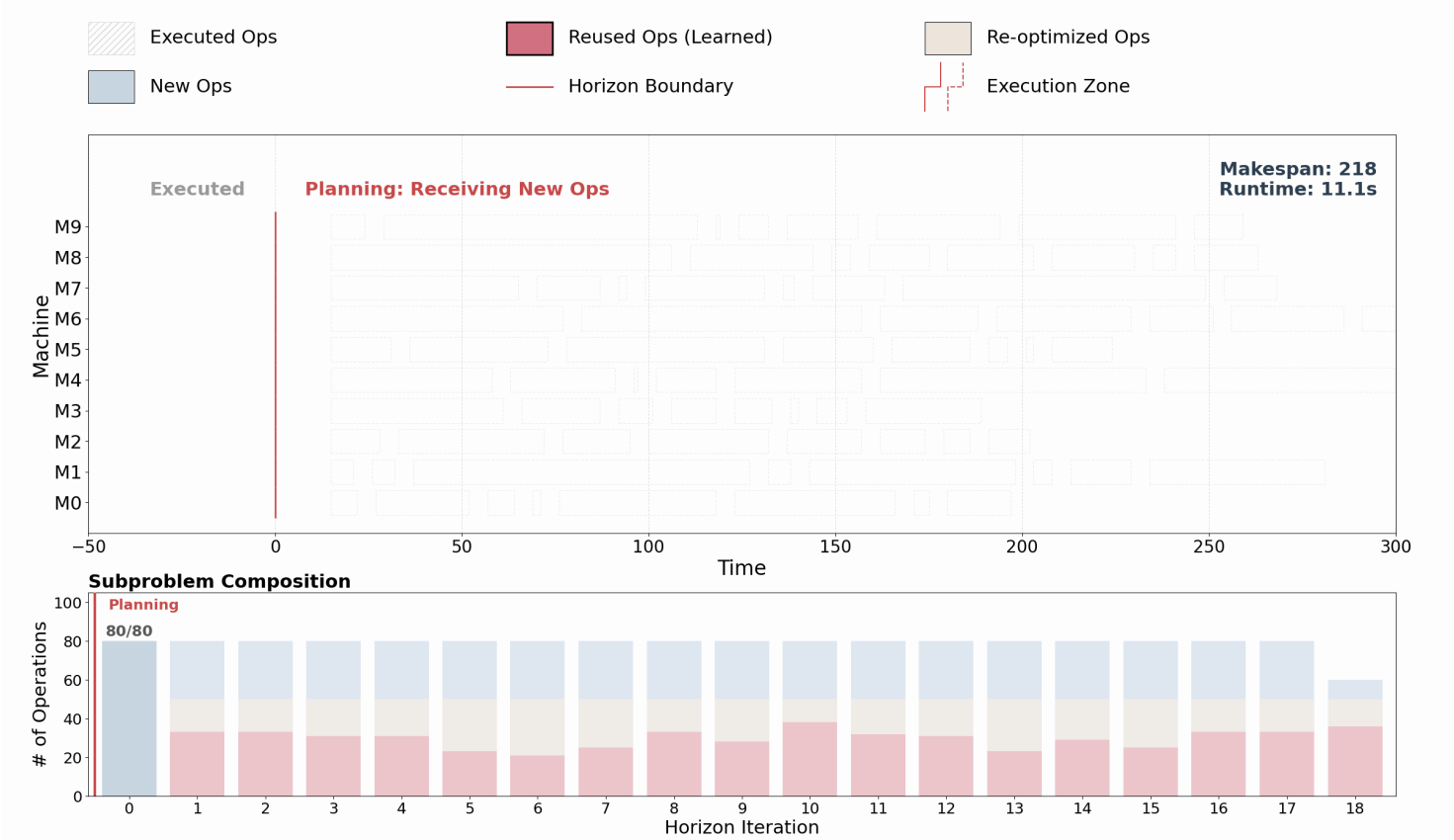
L-RHO (Ours)



- Method: Train a deep neural network to predict if a solution variable will change from one subproblem to the next
- Training Labels: Look-ahead oracle

S. Li, W. Ouyang, Y. Ma, and **C. Wu**, "Learning-Guided Rolling Horizon Optimization for Long-Horizon Flexible Job Shop Scheduling," in ICLR, 2025.

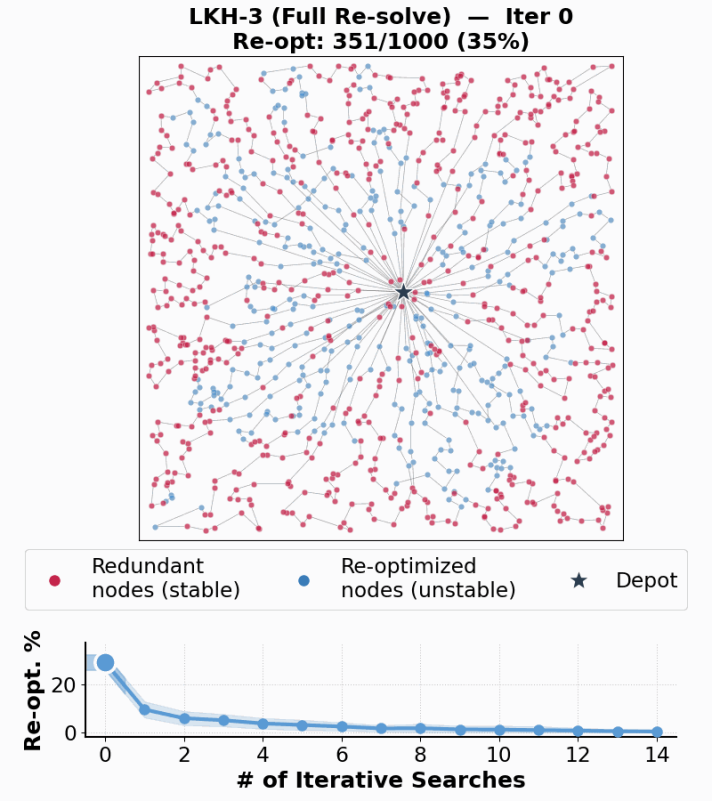
L-RHO for Flexible Job Shop Scheduling



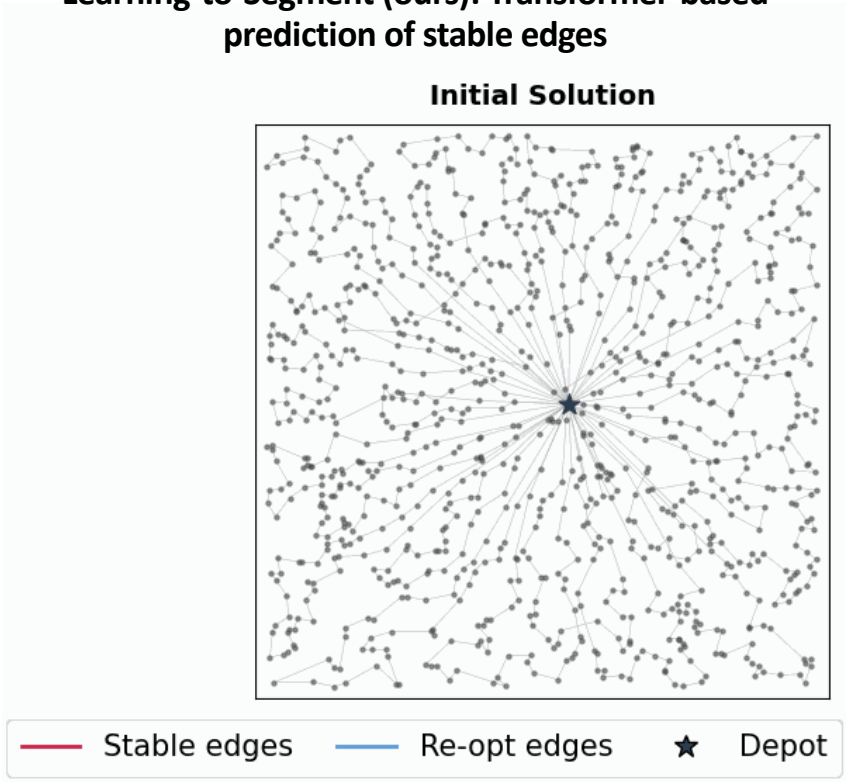
S. Li, W. Ouyang, Y. Ma, and **C. Wu**, "Learning-Guided Rolling Horizon Optimization for Long-Horizon Flexible Job Shop Scheduling," in ICLR, 2025.

Learning to Reuse for Large Vehicle Routing

State-of-the-art Solver LKH (metaheuristic)



Learning-to-Segment (ours): Transformer-based prediction of stable edges



Results: 7x faster on CVRP with 2000 customers

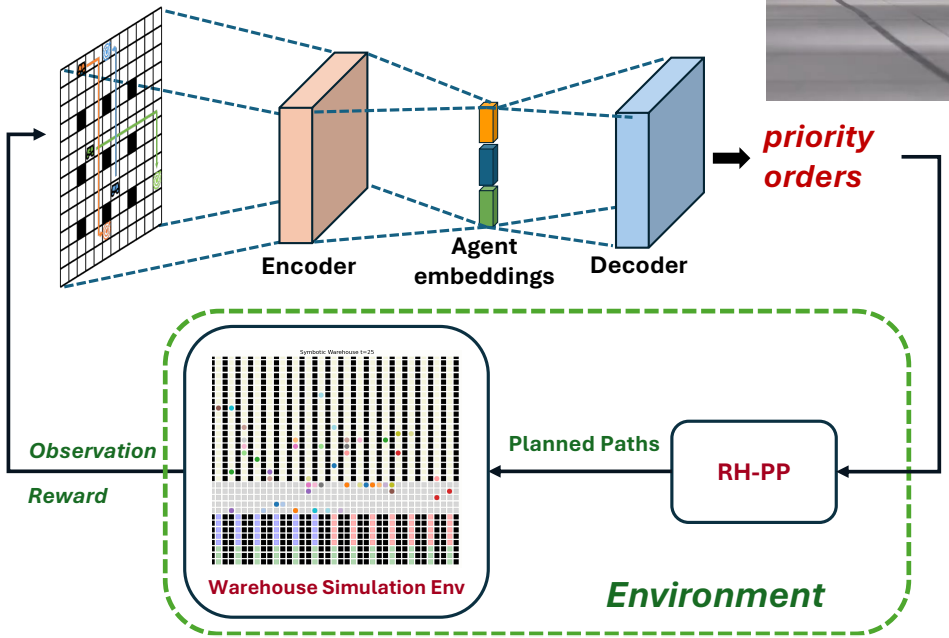
W. Ouyang, S. Li, Y. Ma, and **C. Wu**, "Learning to Segment for Vehicle Routing Problems," International Conference on Learning Representations (ICLR), 2026. **Oral (1%).**

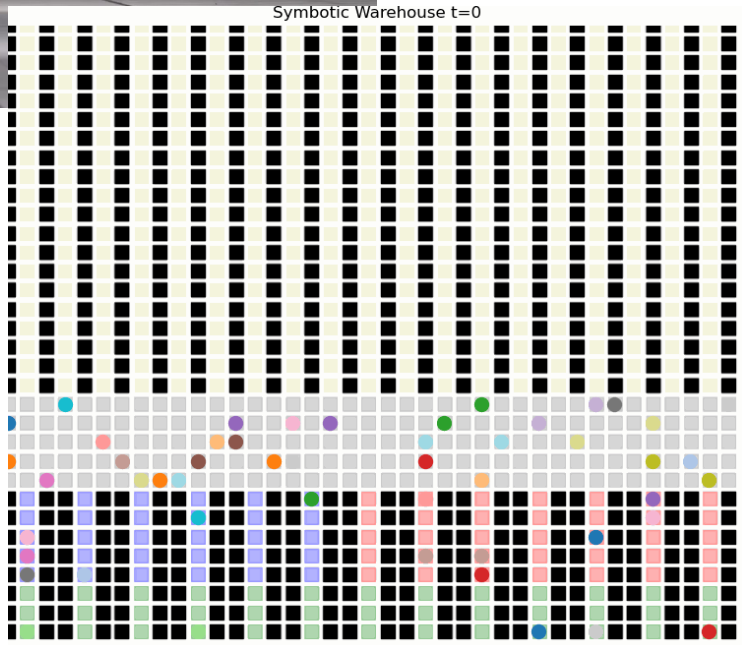
Congestion Mitigation in Automated Warehousing

- Learn **priority order** of agents
- Method: Deep RL-guided prioritized planning
- **Results: +20% throughput on Symbotic-style warehouses**



symbotic



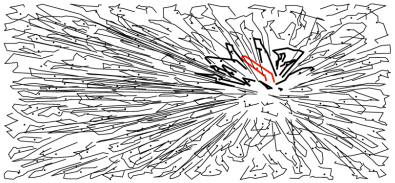


H. Zheng, Y. Ma, B. Araki, J. Chen, and **C. Wu**, "Learning-guided Prioritized Planning for Lifelong Multi-Agent Path Finding in Warehouse Automation," *Journal of Artificial Intelligence Research (JAIR)*, 2026.

Learning-guided combinatorial optimization

Contribution: **Deep learning can accelerate combinatorial optimization solvers by 2-10x.**

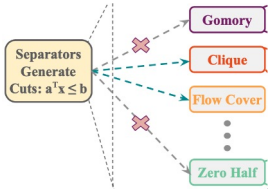
Learning to Focus and Prioritize Search

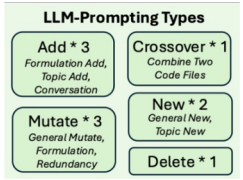


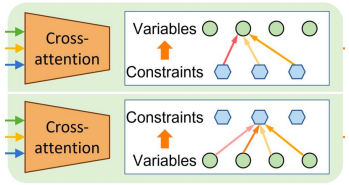


NeurIPS21 **Spotlight (<3%)** ICLR24 JAIR26

Learning for Mixed-Integer Linear Programming

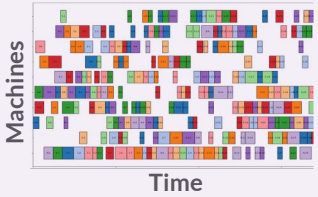


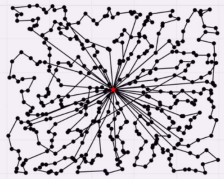




NeurIPS23 ICLR25 ICML26

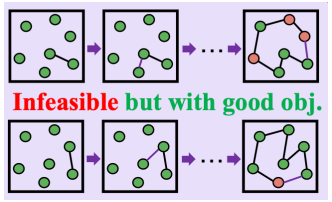
Learning to Reuse Across Iterations





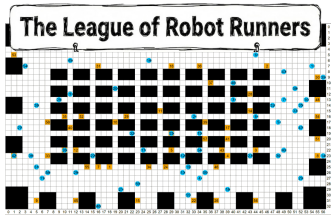
ICLR25 ICLR26 **Oral (1%)**

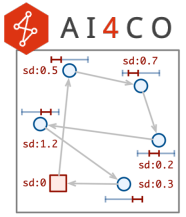
Learning to Repair Solutions



ICLR26

Benchmarks & Competitions



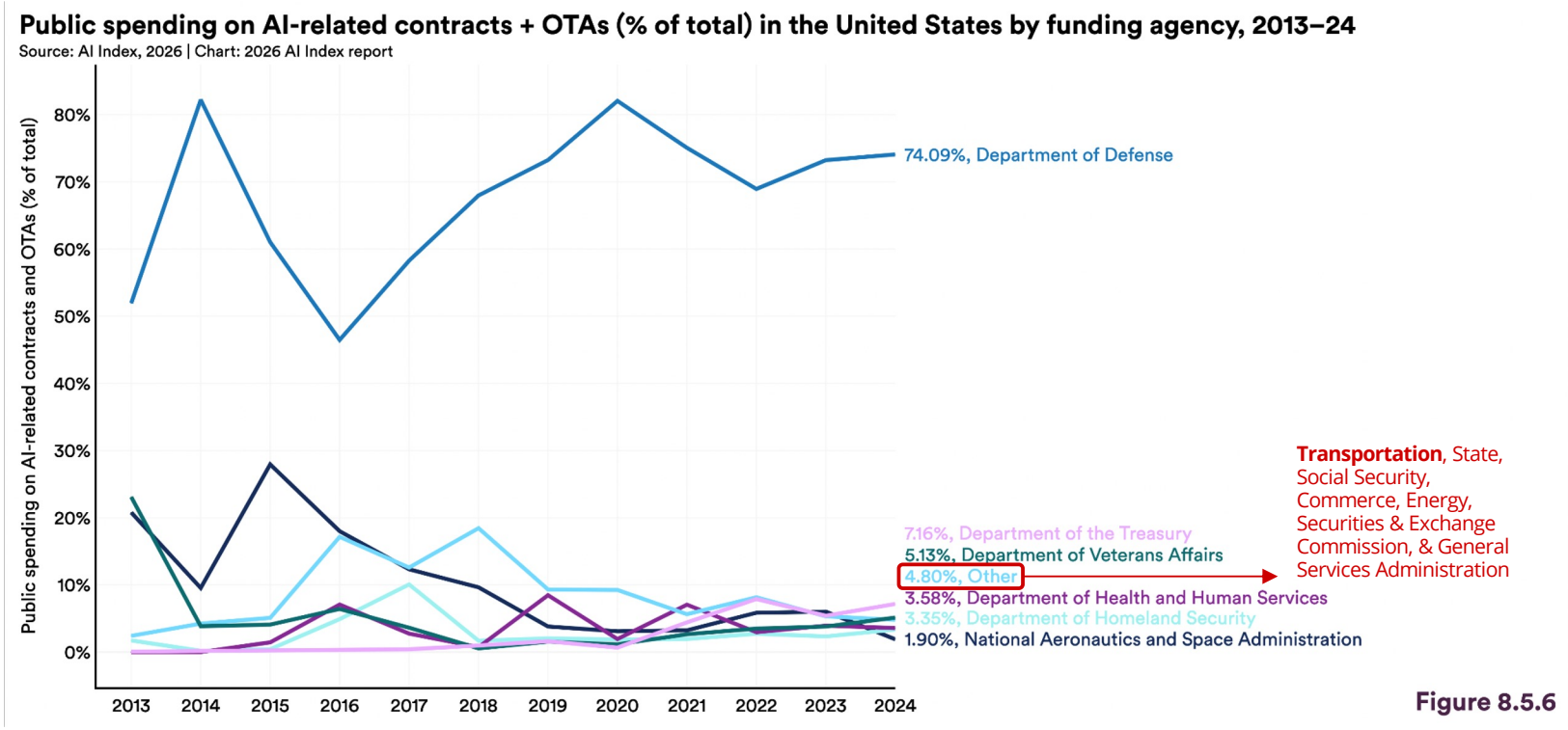


ICAPS24 KDD25 **Oral (9%)**

Modest data and compute (1,000 instances, 1 day on V100); **Fairly generalizable**.

Final remarks

It's early days for AI in transportation



[1] S. Sha et al., "The AI index 2026 annual report," in The AI index 2026 annual report, 2026. [Online]. Available: https://hai.stanford.edu/ai-index/2026-ai-index-report

Synthesis of key considerations

- **Theory of change** for decarbonizing transportation
  - Decarbonizing transportation **lacks a central economic champion** to push for action
  - Success requires a **broad coalition of stakeholders** with **climate-aligned priorities**
    - **China** → industrial policy → **energy security** → electrification
    - **Working and middle class** → votes → **cost & convenience** → modal shift
    - **Corporations** → operations → **cost** → efficiency improvements
  - Think: what climate actions coincide with the many priorities in transportation?
    - Personal example: **Utah** → regulate driving → **air quality** → eco-driving
- **When is AI useful?**
  - AI can help 1) build data-driven models of transportation processes, 2) optimize models to find good solutions, 3) automate digital workflows, 4) enable robotic automation
  - The toughest part is often figuring out when one of those is a key bottleneck and how it integrates with the rest of the solution/system

Entry points and next steps

Get Involved: Sustainable Transport

- Bridging Transportation Researchers (BTR)
  - Zero carbon, zero cost transportation research conference (**Virtual, Aug 12-13!**)
- National Association of City Transportation Officials (NACTO)
  - Association of North American cities and transit agencies, advancing safety, sustainability, access, and equity in cities
  - Designing Cities Conference (next edition: Nashville, May 2027)
- Transportation Research Part D: Transport and Environment
  - Top field journal dedicated to environmental impacts of transportation, policy responses to those impacts, and their implications for the design, planning, and management of transportation systems
- Transportation Research Board (TRB) Annual Meeting
  - TRB is part of the National Academies of Science, Engineering, & Medicine
  - Central professional ecosystem in North America (Washington DC, every January)
  - Standing Committee on Transportation Energy Data and Analysis (AED18) (previous meeting)
    - Focus: research and innovation related to data and analytical methods for measuring energy use, fuel consumption, and efficiency in transportation systems.



Get Involved: AI + Transport

- Transportation Research Part C: Emerging Technologies
  - Top field journal addressing development, applications, and implications, in the field of transportation systems and emerging technologies
- IEEE Transactions on Intelligent Transportation Systems
  - Top field journal covering fundamental and applied research on all scientific and technical aspects of modern transportation systems
- Transportation Research Board (TRB) Annual Meeting
  - Central professional ecosystem in North America (Washington DC, every January)
- IEEE International Conference on Intelligent Transportation Systems (ITSC) (upcoming: Naples, Italy, Sep 15-18)
  - The main field-specific AI/ITS conference





Awesome RERITE: A curated list of awesome open datasets and benchmarks in transportation research

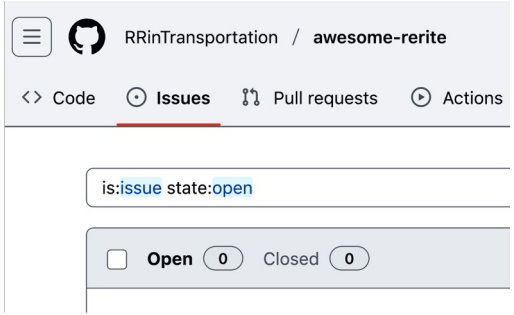
https://www.rerite.org/awesome-rerite

Tooling & Workflows

- **Global Urban Street Networks** — updated and published repository containing street network models for all 10,351 urban areas worldwide (GraphML, GeoPackages, and node/edge lists), plus indicators and metadata. Journal article: https://doi.org/10.1177/23998083261446991. Source code: https://github.com/gboeing/street-network-models.
- **OSMnx** — award-winning toolkit by Geoff Boeing for downloading, modeling, and analyzing street networks.
- **osm2gmns** — converts OpenStreetMap data into GMNS format; developed by Jiawei Lu and Xuesong (Simon) Zhou.
- **DTALite** — ASU Transportation AI Lab's macroscopic/mesoscopic AMS library that natively reads GMNS.
- **DTA** — Dr. Ke Han's open-source dynamic user equilibrium solver (see Networks and Spatial Economics, 2019).
- **OSRM** — C++14 routing engine providing lightning-fast shortest path queries.

Find more to share and contribute? It's easy! We'd like to promote more and share more with the community!

Open an issue at the github page or email us!



Transportation research open science explorer



Call for Interest: Special Issue on Transportation Evaluations & Datasets (TR Part C & T-ITS)

Call for Interest: Transportation Evaluations & Datasets

RERITE is excited to announce a new initiative: In preparation for a Special Issue on "**Evaluations & Datasets for Transportation Research**", please let us know your evaluations & datasets **needs and wish list**. The special issue will be published with Transportation Research: Part C (TRC) and/or IEEE Transactions on Intelligent Transportation Systems (T-ITS).

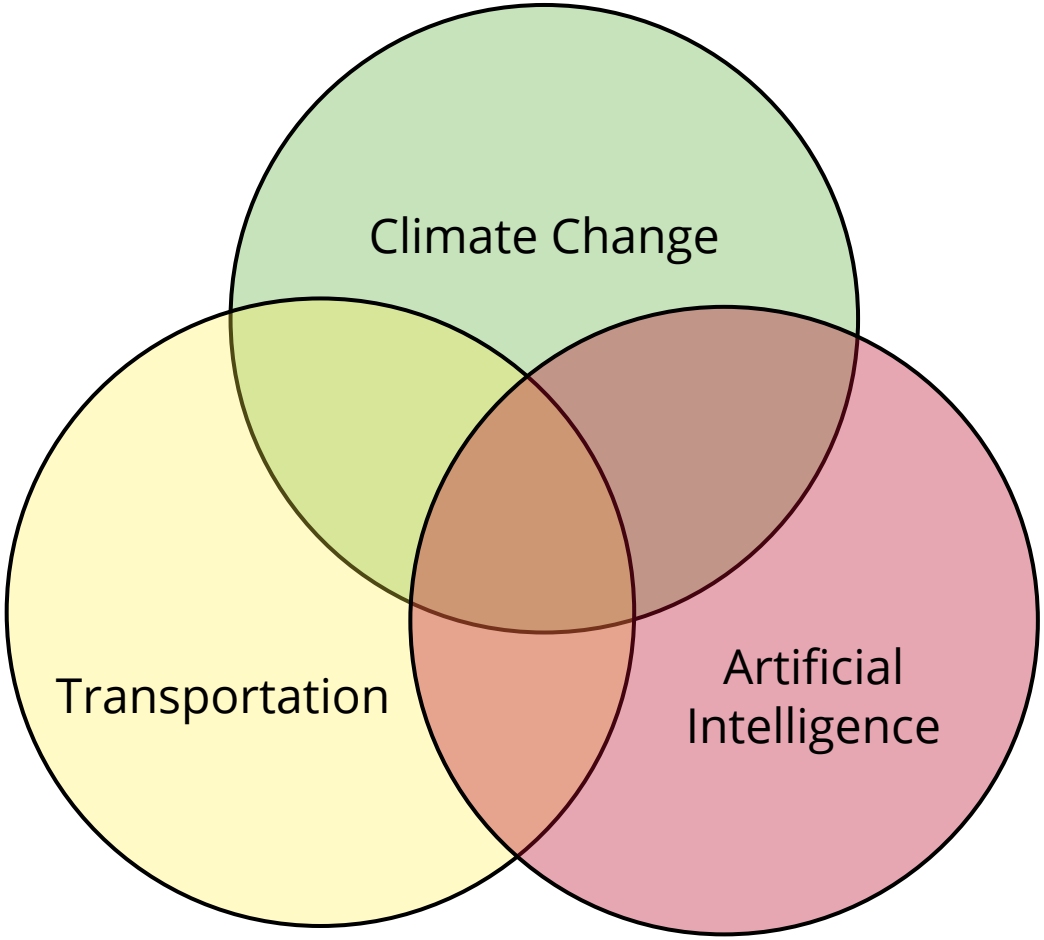
You are welcome to fill out the form as many times as you have wishes. Please include as much context as you can; the more context you provide, the more effectively we will be able to scope and target the special issue.

Do not worry about whether someone else will submit the same topic. The more a topic is expressed as a need, the more we can understand the needs of the community!

This initiative is modeled after the NeurIPS 2026 Evaluations & Datasets Track Call for Papers.

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Appendix

Additional topics

- AI for climate mitigation in commercial aviation
  - Sandalow, David B. et al., “Artificial Intelligence for Climate Change Mitigation Roadmap (Second Edition),” (Chapter 7: Commercial Aviation), Nov. 2024, doi: 10.7916/2J4P-NW61.
- AI for climate mitigation in shipping
  - World Economic Forum, “Intelligent Transport, Greener Future: AI as a Catalyst to Decarbonize Global Logistics.” Jan. 2025. https://seminarleadership.ibo.pe/case-02/.
- AI for adaptation and resilience in transportation
  - Costa, Miguel, et al. “Artificial Intelligence for Climate Adaptation: Reinforcement Learning for Climate Change-Resilient Transport.” arXiv, 2026. https://doi.org/10.48550/arXiv.2603.06278.