ENGLISH Summary

Artificial intelligence for strategic transport planning - opportunities and limitations

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The increasing availability of large and continuous data sources in transport (sensor data, app/mobile data, etc.) makes machine learning models highly attractive for operational planning and Intelligent Transport Systems (ITS). However, the potential for machine learning in strategic transport planning is less clear. This is because strategic planning requires the ability to predict the future in various scenarios, many of which involve mechanisms that have not yet been observed and are therefore unrecognizable to machine learning models based on training data. In this report, we map out the current and potential future use of artificial intelligence (AI) and machine learning for strategic planning. Our assessment indicates that machine learning and generative AI have the greatest potential to improve the empirical data foundation for transport planning, as well as (partially) automate and streamline certain tasks related to analysis, administration, and stakeholder management. AI is unlikely to replace the function of transport models and simulation models, as machine learning models are not well suited for making long-term forecasts or analyzing counterfactual measures.

This report summarizes the findings of a project aimed at mapping the use and potential of artificial intelligence (AI) in strategic transport planning. Strategic transport planning has a longer planning horizon than operational planning. While operational planning is used for daily operations and traffic management, short-term transport demand forecasting, and planning short-term transport services, strategic transport planning is relevant for large infrastructure projects, long-term policy development, or analyzing new measures. The latter is particularly relevant in connection with the National Transport Plan and strategies for achieving climate goals. Regarding AI and machine learning, strategic transport planning can be defined as transport analyses where there is insufficient training data from actual observations.

Since AI development is progressing rapidly, it is relevant to mention that this report was written around the turn of 2024/2025 and thus represents the knowledge available at that time (including January 2025). In this report, we focus on machine learning models based on neural networks and deep learning, specifically on methods that can be used to classify and predict various types of data, models, and products within generative AI.

The assessments in this report are based on a literature review and information gathering from the internet as well as internal and external documents. The project timeline did not allow for systematic expert interviews.

Figure S1 attempts to provide a comprehensive overview of the evaluations made in this report.

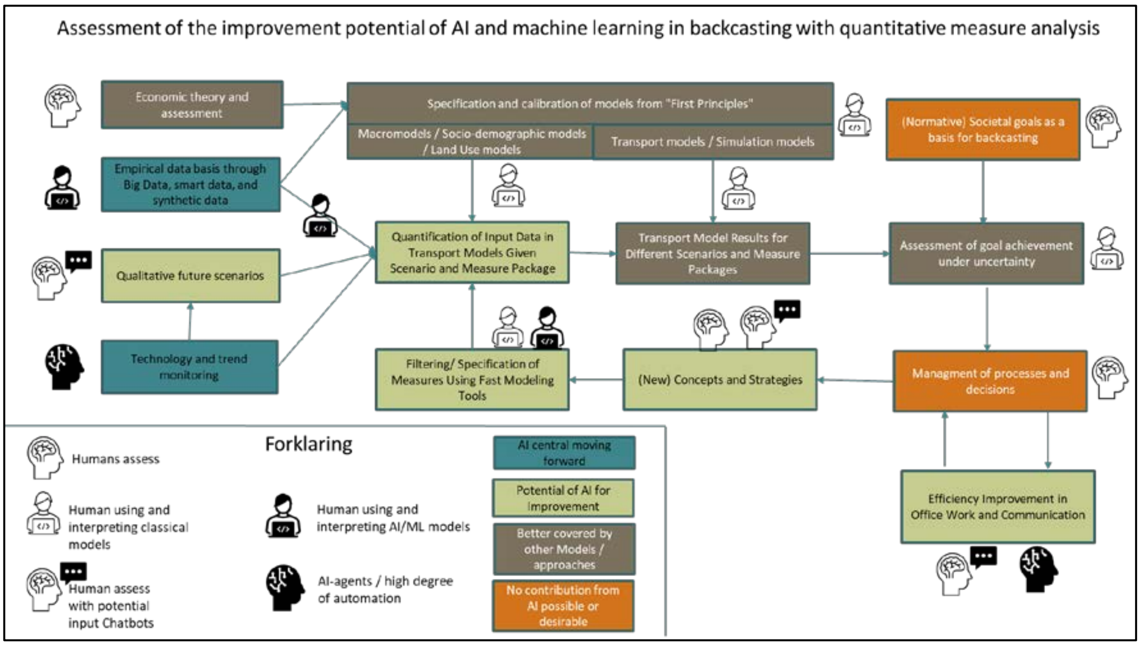

Figure S1: Summary of the assessments made in the project.

We begin (at the top right of the figure) with the **formulation of societal goals** as the foundation for transport planning. Such goal formulation can be seen as an application of an (implicit or explicit) backcasting process. We assess goal formulation as a task for which AI is unsuitable. These goals should be defined by citizens themselves (therefore marked in orange in the figure), ideally through democratic processes, and automation of this process should be avoided.

Societal goals should then serve as the basis for **assessing goal achievement** under uncertainty. This should largely rely on systematic models, principles, and tools. Here, human decision-makers use classical approaches that are readily interpretable and explainable. AI and machine learning are not a natural fit for this step.

The assessment of the expected achievement of societal goals should guide **decision-making** and prioritization. Again, this task should be reserved for humans.

Prioritizations must be implemented in planning processes, where we see significant potential for AI systems to **streamline office work and communication** (box on the lower right). For some tasks, AI can serve as a tool for humans, while other tasks may be more extensively automated. Although the adoption of AI may take time and involve challenges and risks, this appears to be a "natural" progression and is consistent with the government's objective of integrating AI across all public agencies in the long run.

In a backcasting approach, it is crucial to iteratively update and refine strategies to maximize the likelihood of achieving goals, even under changing conditions. **New concepts** for measures and strategies should originate from humans, but we see potential for (reasoning-based) language models to identify logical and—if necessary—creative new solutions.

Strategies must be broken down into a set of measures. In **screening potential measures**, preliminary impact assessments and predictions may be needed. Faster versions of RTM are being developed for this purpose. Additionally, machine learning models—such as meta-models described in this report—may offer opportunities.

For the **development of future scenarios** relevant to transport planning, we see the potential for language models to be used as brainstorming partners (with humans in control), while the integrated task of trend and technology monitoring could be largely automated.

Machine learning is expected to play a key role in **establishing better empirical data foundations** for the specification and calibration of models. This applies to both macroeconomic/land-use models and transport models, which are referred to in this report as "first-principles models." These models are based on economic theory, typically interpreted by humans (box at the top left).

We have assessed whether machine learning models can replace models based on first principles, such as macroeconomic models, transport models (RTM), and simulation models. These models are built on mathematical functions (often grounded in economic theory) and fundamental mechanisms, which represent a simplified but theoretically well-founded understanding of what is physically possible. Such models often exhibit strong generalization capabilities compared to data-driven approaches, which rely more heavily on observed patterns in data. Since machine learning models are generally not well suited for long-term forecasts and counterfactual analyses, **we do not believe that macroeconomic models and transport models can be replaced by artificial intelligence**. However, the potential to integrate transport models and AI (beyond improving data foundations) is considered an emerging research frontier that warrants further investigation.

A key discussion point regarding the application and significance of new technologies in different fields is the time dimension. When will deep learning and generative AI be mature enough for active use in strategic transport planning?

The Gartner hype cycle for technology expectations illustrates how we often overestimate the short-term effects of new technology while underestimating its long-term impact. Short-term overestimation is reflected in the "peak of **inflated expectations**" in the Gartner hype cycle, where optimism about the technology's potential dominates. On the other hand, the "plateau of productivity" represents the point where the technology's long-term and transformative impact becomes evident, often far exceeding initial scepticism. Generative AI reached the peak of the hype cycle in 2023 and was already moving into the "trough of disillusionment" in 2024. According to Gartner's analysis, it will take another 2–5 years before generative AI reaches its full and stable potential.

This is not only due to technical reasons (as the technology is still somewhat immature for certain tasks), but also because adaptation takes time for employees. Additionally, systemic adaptation (e.g., within an organization or company) can take longer than individual adoption. Some employees may quickly adopt new technologies but changing processes and workflows across teams can take much longer.

This report has aimed to provide an initial mapping of the opportunities and limitations of using artificial intelligence for strategic transport modeling and planning. However, many open questions remain that should be further investigated, and follow-up projects should be initiated to explore specific possibilities in more detail.

Regarding AI implementation in the workplace, it is crucial to better understand the barriers to AI adoption in organizations. A lack of knowledge and training in AI can be a significant obstacle, which could justify **prioritizing further education for employees**.

Several research questions merit further exploration**. How machine learning can be combined with classical transport models is a key topic** for improving quantitative methods. Additionally, the potential of combining simulation models, reinforcement learning, and generative agents should be examined more closely. With today's computational capacity and technology, it is possible to conduct large-scale societal simulations in digital twins, which could pave the way for future transport models that better replicate real-world processes.

Language models and generative AI also have many **potential applications in qualitative analyses**, including brainstorming, scenario development, and writing assistance. However, there is no clear "best practice" in this area yet. Further research and experimentation may be necessary to understand how human-AI collaboration can be best structured.

Given the rapid pace of technological development, there is a risk that research—including this report—will quickly become outdated. It may therefore be beneficial to continuously address this issue. Considering the potentially significant changes and societal disruptions that advanced AI may bring, it seems prudent to **allocate resources for monitoring developments and identifying new improvement opportunities** enabled by artificial intelligence.