When do autonomous vehicles solve or exacerbate different urban mobility problems?

A simulation study exploring modal shifts and system-level impacts in dense urban environments

By

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All code, data and figures are available at: https://github.com/EwoutH/urban-self-driving-effects

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Preface

What's fascinating about researching personal transportation is that almost everyone has not only experience with it, but also strong opinions and frustrations. These rarely align - what one person loves can be another's major irritation. Often these issues involve scaling or common pool problems, making them incredibly complex to fully understand.

Transportation, at its core, is about the division of resources: land, energy, money, time, noise, and environmental impact. While new innovations are frequently celebrated, they almost always come with significant drawbacks or scaling problems. True dominant solutions are rare; there are no silver bullets.

Self-driving cars, and specifically the upcoming robotaxi sector, will follow this pattern. I believe they will revolutionize the market, making some people declare them the best invention since sliced bread while others insist that "vroeger was alles beter", as we say in Dutch. This is typical of paradigm-shifting transportation modes (and even some that aren't - remember the overwhelming stacks and stacks of shared bikes?).

This research aims to provide a broader perspective on autonomous vehicles and, hopefully, prevent some of the avoidable problems this new mode of transport will introduce.

No research stands alone, and I'm indebted to several people. For enabling my research: Igmar Coenen, who developed the Verkeersmodel MRDH and answered countless questions; Toru Seo, developer and maintainer of UXsim, for creating and supporting his remarkable traffic simulation package; and many more random people from Nebraska that has been thanklessly maintaining projects since 2003.

We truly stand on the shoulders of giants.

I'm grateful to my supervisors, Jan Anne Annema and Jan Kwakkel - or as I addressed them in emails: Jan (Anne). They gave me considerable freedom to explore this research in my own way, accepting my sometimes unconventional methods. Jan Anne responded to my oblivious questions not just with "Google this" but with actual papers and materials, while Jan contributed both his unmatched technical expertise and impressive patience in structuring my occasionally very incoherent ramblings.

Special thanks to Christiaan Ouwehand, one of my closest friends, for reviewing and providing feedback on numerous drafts and ideas, and to my father, for reading every word diligently, sometimes twice, and being genuinely excited about it.

Finally, I want to thank my support network, in the largest extend. You have seen me balls to the wall excited, deeply frustrated, and everything in between. You have been there, indulged me, supported me. You know who you are. Thanks.

Ewout ter Hoeven
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Contents

Abstract

Background: The introduction of autonomous vehicles (AVs) could fundamentally transform urban transportation, but their system-level effects on cities remain poorly understood. Previous research has focused primarily on individual adoption decisions or specific impacts like congestion, without capturing the complex interactions between adoption patterns, modal shifts, and transportation system performance.

Goal: This study investigates how autonomous vehicles might affect urban mobility problems, considering both modal shifts and induced demand, and examines which policies could effectively mitigate potential negative impacts while preserving benefits.

Method: An agent-based model combined with mesoscopic traffic simulation was developed to simulate travel behavior in Rotterdam, Netherlands. The model integrates empirical data on population distribution, travel patterns, and network characteristics with a mode choice framework accounting for heterogeneous time valuations. A full-factorial analysis explored 144 scenarios varying AV costs, perceived time value, space efficiency, and induced demand. Eight representative scenarios were then tested against nine policy combinations including congestion pricing and speed reductions.

Results: AV adoption patterns appear to depend more strongly on space efficiency than cost or comfort advantages. A critical threshold around a density factor of 0.5 (compared to conventional vehicles) emerged - below this threshold, high AV adoption can maintain system performance, while above it, increased adoption tends to degrade network performance regardless of other characteristics. The model also revealed that AVs compete more directly with sustainable transport modes than with private cars, potentially undermining urban sustainability goals. Traditional policy interventions showed limited effectiveness across different scenarios, with localized restrictions proving particularly inadequate for managing system-level impacts.

Conclusions: Autonomous vehicles may represent neither an inherent solution nor an inevitable problem for urban mobility. Their impact appears likely to depend on the interaction between their operating characteristics, adoption patterns, and policy frameworks. The significant variations between potential futures - ranging from improved mobility to system strain - emphasize the importance of proactive policy consideration in AV development. Results suggest that cities should focus on ensuring space-efficient AV operations rather than just regulating costs or access, while developing more dynamic and comprehensive policy frameworks to manage the transition.

Keywords: autonomous vehicles, urban mobility, agent-based modeling, traffic simulation, mode choice, transportation policy, modal shift, induced demand

1. Introduction

The introduction of the automobile fundamentally transformed human transportation and urban development in the 20th century. While providing unprecedented mobility and economic opportunities, the widespread adoption of cars has also led to significant challenges in urban environments. These include traffic congestion, parking scarcity, air and noise pollution, and safety concerns for pedestrians and cyclists. As we progress into the 21st century, a new technological revolution is on the horizon: self-driving cars.

Self-driving cars, also known as autonomous vehicles (AVs), represent a potential paradigm shift in urban transportation. Unlike the gradual evolution of traditional automobiles, AVs promise to radically alter not just how we drive, but also patterns of vehicle ownership and use. The transition from private ownership to a Mobility-as-a-Service (MaaS) model, where self-driving "robotaxis" become the dominant form of motorized road transport, could reshape our cities in profound ways.

Proponents of AVs highlight numerous potential benefits. For individual travelers, the ability to engage in other activities while in transit could significantly alter the perceived cost of travel time. From an urban planning perspective, the promise of solving pervasive parking problems is particularly appealing, as AVs could simply move on to their next passenger instead of occupying valuable urban space. Furthermore, optimized routing and platooning capabilities could increase road network efficiency and potentially improve safety. Fagnant & Kockelman (2015) suggest that AVs could reduce crashes by up to 90% through elimination of human error, while also improving fuel efficiency and reducing congestion through smoother traffic flow. Meanwhile, research from Duarte & Ratti (2018) suggests that shared autonomous vehicles could provide the same mobility with just 30% of the current vehicle fleet in cities like Singapore.

However, the introduction of AVs also raises important questions and potential concerns. While each individual AV might offer improvements over traditional cars in terms of efficiency and environmental impact, the aggregate effect on urban systems remains uncertain. Historical precedent suggests that improvements in transportation technology often lead to induced demand, resulting in increases in total distance traveled.

As Lee et al. (1999) explain, it's crucial to distinguish between induced traffic and induced demand when considering transportation improvements. Induced traffic refers to short-run changes in travel patterns - movements along an existing demand curve as travelers respond to reduced travel costs. Induced demand, on the other hand, represents long-run structural changes that shift the entire demand curve, such as land use changes or economic development spurred by improved accessibility. AVs could generate both: immediate behavioral changes through lower perceived travel costs and longer-term systemic changes by enabling new travel patterns.

Recent research has begun to explore these system-level impacts, but significant gaps remain in our understanding. Talebian & Mishra (2018) developed sophisticated models predicting AV adoption based on diffusion of innovations theory, incorporating social networks and peer effects. However, their work focused primarily on individual adoption decisions rather than collective urban impacts, and didn't account for the complex interactions between adoption patterns and transportation system performance.

Fagnant & Kockelman (2015) provided a comprehensive review of opportunities and barriers for AV implementation, estimating potential societal benefits of $2,000 to $4,000 per vehicle annually. However, their analysis relied heavily on expert opinion and theoretical arguments rather than simulation of actual urban systems. The dynamic effects of AV adoption on travel behavior and urban mobility patterns remained largely unexplored.

Metz (2018) specifically investigated congestion impacts, highlighting how the self-regulating nature of urban traffic means that congestion benefits might be temporary as improved mobility attracts previously suppressed trips. However, this work focused mainly on conceptual arguments rather than quantitative analysis, and didn't explore how different AV operating characteristics might influence these dynamics.

Perhaps most concerningly, emerging evidence suggests that AVs might compete more directly with sustainable transport modes than with private cars. In their analysis of recent transit ridership declines, Graehler et al. (2019) found that the introduction of ride-hailing services was associated with a 1.7% decrease in bus ridership per year and a 1.3% decrease in heavy rail ridership. This suggests that new mobility technologies may primarily attract users away from public transit rather than reducing private car use - a pattern that could be even more pronounced with cheaper, more convenient autonomous vehicles.

What's missing from current research is an integrated analysis that connects individual adoption decisions with system-level transportation impacts while accounting for the spatial and temporal dynamics of urban mobility. Previous studies have either focused on adoption patterns without detailed transportation modeling (Talebian & Mishra, 2018), analyzed potential impacts without modeling adoption mechanisms (Fagnant & Kockelman, 2015), or explored specific effects like congestion without capturing the full range of system interactions (Metz, 2018).

This study aims to fill this gap by developing an agent-based model that combines detailed transportation simulation with dynamic adoption behavior. By modeling individual travel decisions, their collective impact on system performance, and the resulting feedback on future decisions, we can better understand how the introduction of AVs might reshape urban mobility patterns. Our approach is novel in three key ways:

1. It integrates mode choice decisions with mesoscopic traffic simulation, allowing us to capture both immediate behavioral responses and resulting system-level effects
2. It explicitly models competition between AVs and sustainable transport modes like cycling and public transit, addressing concerns raised by empirical studies of similar mobility innovations
3. It explores how different AV operating characteristics (like space efficiency and perceived time value) might create distinct future scenarios, enabling more nuanced policy analysis

This approach allows us to address our primary research question:

> *Which undesired urban problems might the introduction of self-driving cars cause, considering the modal shift and induced demand, and what policies can effectively mitigate undesired impacts?*

To answer this overarching question, we explore several key sub-questions:

- **A.** How can a traffic and mode choice model represent the system that shows the tradeoffs and potentially undesired effects of self-driving cars?
- **B.** How could self-driving cars be adopted under different future uncertainties?
- **C.** Which potential undesired system effects are amplified and which are reduced by the introduction of self-driving cars?
- **D.** Which potential policies are most effective in minimizing which undesired system effects while maintaining benefits under different uncertainties?

By addressing these questions, this research aims to provide insights for urban planners, policymakers, and transportation engineers as they prepare for the advent of self-driving cars. Understanding the potential system-wide effects of AVs is crucial for developing proactive strategies to maximize their benefits while mitigating unintended negative consequences in our urban environments.

The remainder of this thesis is structured as follows: Section 2 describes the methodological approach, including the rationale for combining agent-based modeling with mesoscopic traffic simulation. Section 3 presents the model design and validation, demonstrating how the system can be represented to explore AV adoption effects. Section 4 details the experimental design used to investigate different scenarios and policy interventions. Section 5 presents the results of these experiments, examining AV adoption patterns, system-level effects, and policy effectiveness. Finally, Section 6 discusses the implications of these findings for urban transportation planning and policy, while Section 7 concludes with key insights and recommendations for future research. Supporting material is provided in five appendices: Appendix A provides a complete model description following the ODD protocol, Appendix B lists key modeling assumptions, Appendix C discusses model limitations, and Appendix D details the experimental setup.

2. Methods

This study employs agent-based modeling (ABM) combined with mesoscopic traffic simulation to investigate the system-level effects of autonomous vehicle adoption in urban environments. Agent-based modeling was chosen over alternatives like pure equation-based approaches or aggregated flow models because it allows explicit representation of heterogeneous decision-making and captures emergent system behavior from individual choices. This is particularly important for studying AV adoption, where individual-level factors like value of time preferences and car ownership interact with system-level effects like congestion to create complex feedback loops. Alternative methods like system dynamics could capture some feedback mechanisms but would miss the spatial granularity and heterogeneity essential for understanding urban mobility patterns.

The model was developed following the Modeling & Simulation lifecycle (Law, 2014) and structured according to the ODD (Overview, Design concepts, Details) protocol (Grimm et al., 2020). The complete ODD protocol description is provided in Appendix A. Peer and supervisor feedback was incorporated throughout the development process, and Ockham's razor was applied to minimize unnecessary complexity while maintaining essential dynamics.

The modelling approach in this study can be seen as having three interconnected layers that address the research subquestions. The first layer consists of dynamic processes - the daily movements of travelers choosing their transport modes and navigating through traffic, with continuous feedback between individual decisions and network conditions. The second layer contains experimental variables that represent key uncertainties about autonomous vehicles (like their cost and efficiency) and potential policy interventions (such as congestion pricing). While these variables remain constant during each simulation, they are systematically varied between simulations to explore different future scenarios. The third layer provides validated baseline data, including population distribution, road networks, and travel patterns, which remains constant across all scenarios to ensure meaningful comparisons.

These layers build upon each other to systematically address each research subquestion: the dynamic processes layer demonstrates how to represent the system (subquestion A), the experimental variables layer enables exploration of adoption patterns (B) and system effects (C), while both layers together allow testing policy interventions (D). This layered structure ensures that while scenarios explore uncertain aspects of future mobility, they remain grounded in validated current travel patterns and infrastructure constraints.

For subquestion A (how to represent the system), the model builds upon the traditional four-step transportation demand model (McNally, 2007), but implements it within an agent-based, discrete-event controlled framework. The mesoscopic traffic simulation approach was chosen as a middle ground between microscopic and macroscopic models. While microscopic simulation could provide more detailed vehicle interactions, it would be computationally prohibitive at the city scale needed for this research. Conversely, macroscopic models would miss important dynamics like intersection delays and route choice that affect system performance. The mesoscopic approach, a middle-ground approach between microscopic individual vehicle modeling and macroscopic flow-based modeling, provides sufficient detail to capture congestion effects and travel time variations while remaining computationally tractable for large-scale scenario analysis.

The first two steps — trip generation and trip distribution — are derived from empirical data: trip generation rates from the Dutch National Travel Survey (ODiN 2023) and trip distribution from V-MRDH origin-destination matrices. This grounds the model in validated travel patterns while allowing modification of behavioral parameters to explore AV scenarios. The latter two steps — mode choice and route assignment — are modeled dynamically through agent behavior and traffic simulation, enabling investigation of how travelers might respond to new mobility options.

For mode choice, a rational utility-maximization approach based on perceived costs (including both monetary costs and time weighted by individual value of time) was selected over alternatives like random utility models or rule-based approaches. This choice was driven by three key considerations: First, the lack of stated preference data for AVs made calibrating more complex choice models speculative. Second, the research focus on system-level effects meant that capturing broad behavioral patterns was more important than precise individual choices. Third, the value of time framework provides a clear mechanism for exploring how AVs might change travel behavior through reduced perceived time costs. While this approach simplifies some aspects of real-world decision making, it captures the essential trade-offs between time, cost, and comfort that drive mode choice.

This hybrid approach was chosen over alternatives like pure activity-based models because it provides a robust framework for exploring mode choice shifts while maintaining computational tractability. While an activity-based approach might better capture complex trip chains and scheduling decisions, the lack of empirical data about how activities might be restructured around AV availability made such an approach speculative. For this, stated preference (SP) survey data would have been needed, which wasn't available for the modes and spatial and temporal scope of this research. Instead, the model focuses on validated trip patterns while allowing behavioral adaptation through mode choice and routing decisions.

For subquestion B (adoption patterns), the model employs a full-factorial analysis of four key uncertainties: AV costs, perceived value of time in AVs, AV space efficiency, and induced demand. These specific uncertainties were selected based on literature review and stakeholder consultation as the factors most likely to influence adoption patterns or cause interesting system-level effects. The factorial design creates 144 unique scenarios (4×3×4×3 levels), enabling systematic exploration of how these factors interact to drive or inhibit AV adoption. This approach was chosen over alternatives like Monte Carlo or Latin Hypercube sampling because it its simplicity makes scenarios directly comparable and human interpretable between variables variations.

To address subquestion C (system effects), the model collects multiple metrics across all scenarios, tracking both direct transportation impacts (like mode shares and network speeds) and broader urban effects (like parking demand and vehicle kilometers traveled). The mesoscopic traffic simulation component, implemented using a modified version of UXsim 1.6.0, was specifically chosen to balance computational efficiency with adequate representation of congestion and network effects. This level of detail allows examination of both localized impacts and system-wide patterns while remaining computationally feasible for the large number of scenarios explored.

For subquestion D (policy effectiveness), eight representative scenarios were selected from the full scenario space to test nine different policy combinations, creating 72 scenario-policy combinations. The scenarios were chosen to span the range of possible futures identified in the full factorial analysis, while the policies represent different approaches to managing AV adoption, varying in both intervention type (pricing vs. speed control) and spatial scope. This focused approach allows detailed analysis of policy effectiveness while remaining computationally manageable.

The model was implemented in Python using Mesa 3.0.0b1 for agent-based modeling and a modified version of UXsim for traffic simulation. Mesa was selected for its ability to handle large agent populations and flexible scheduling, while UXsim implements Newell's simplified car-following model, providing an appropriate balance between computational efficiency and traffic dynamics representation. Data sources include population and vehicle ownership statistics from CBS, road network data from OpenStreetMap, cycling and public transport travel times from Google Maps API, and origin-destination matrices from the V-MRDH transport model.

Model verification and validation followed a systematic approach combining multiple techniques. Verification included continuous integration testing, git version control with detailed commit messages, and manual validation of key metrics. Validation against current travel patterns used Dutch National Travel Survey (ODiN) 2023 data for mode shares and trip distributions. The simulation represents approximately one million residents of Rotterdam, with each agent representing a platoon of 10 actual travelers for computational efficiency. Section 3.6 dives deeper into this, and a full list of modeling assumptions and their justifications is available in Appendix B, while model limitations and validation challenges are discussed in detail in Appendix C.

The novelty of this approach lies in its integration of multiple modeling scales and data sources. While previous studies have examined either mode choice or traffic simulation aspects of AV adoption, this research combines both within a single modeling framework. This enables analysis of feedback loops between individual travel decisions and system-level performance, capturing emergent behaviors that simpler models might miss.

3. Model description

The model simulates travel behavior in the Rotterdam urban area over the course of one day, focusing on mode choice decisions and their collective impact on the transportation system. It consists of three main components: (1) an agent-based model for traveler decision-making, (2) a mesoscopic traffic simulation for vehicle movements, and (3) a discrete event system for scheduling and coordination, with a lot of data feeding into the model.

This section shows how such a system can be represented, answering subquestion A.

3.1 Spatial and temporal structure and scope

The model is designed to simulate a medium-sized city over the course of a day. Rotterdam was selected as the study area for several key reasons. First, its size (approximately 1 million inhabitants in the study area) makes it large enough to exhibit complex urban mobility patterns while remaining computationally manageable. Second, it currently already faces typical urban transportation challenges including congestion, parking scarcity, and competing demands for limited road space. Third, it offers a diverse transportation ecosystem with well-developed alternatives to car travel, including an extensive public transit network (buses, trams, and metro) and significant cycling infrastructure, making it ideal for studying modal shifts. Fourth, it has relatively high car usage for a major city in The Netherlands, enabling potential model shifts from all modes.

Spatial structure

The spatial structure of the model operates at two complementary scales. At the finer level, the study area is divided into 125 four-digit postal code (PC4) areas, which roughly correspond to neighborhoods. This resolution was chosen because it provides sufficient granularity to have broad heterogeneity in road networks, population densities, car availability and travel patterns. These 125 regions created 125 * (125 - 1) = 15,500 possible origin-destination pairs for trips, which ensures a highly heterogeneous set of travel options for agents. In combination with the relatively large number of agents (a under thousand), which were needed for representative traffic simulation anyway, this reduces stochastic noise.

These postal code areas are nested within 21 larger traffic analysis zones from the V-MRDH transport model, allowing for integration with regional travel demand data and validation against existing mobility patterns.

The road network, derived from OpenStreetMap, comprises 1,575 nodes and 3,328 edges, including all roads from tertiary level upward. This network structure balances detail and computational efficiency - major and minor arterials are included to accurately model traffic flow, while local streets are omitted as their impact on system-level dynamics is minimal. The network also includes planned infrastructure improvements like the new A16 motorway and Blankenburg tunnel to ensure relevance for near-future scenarios.

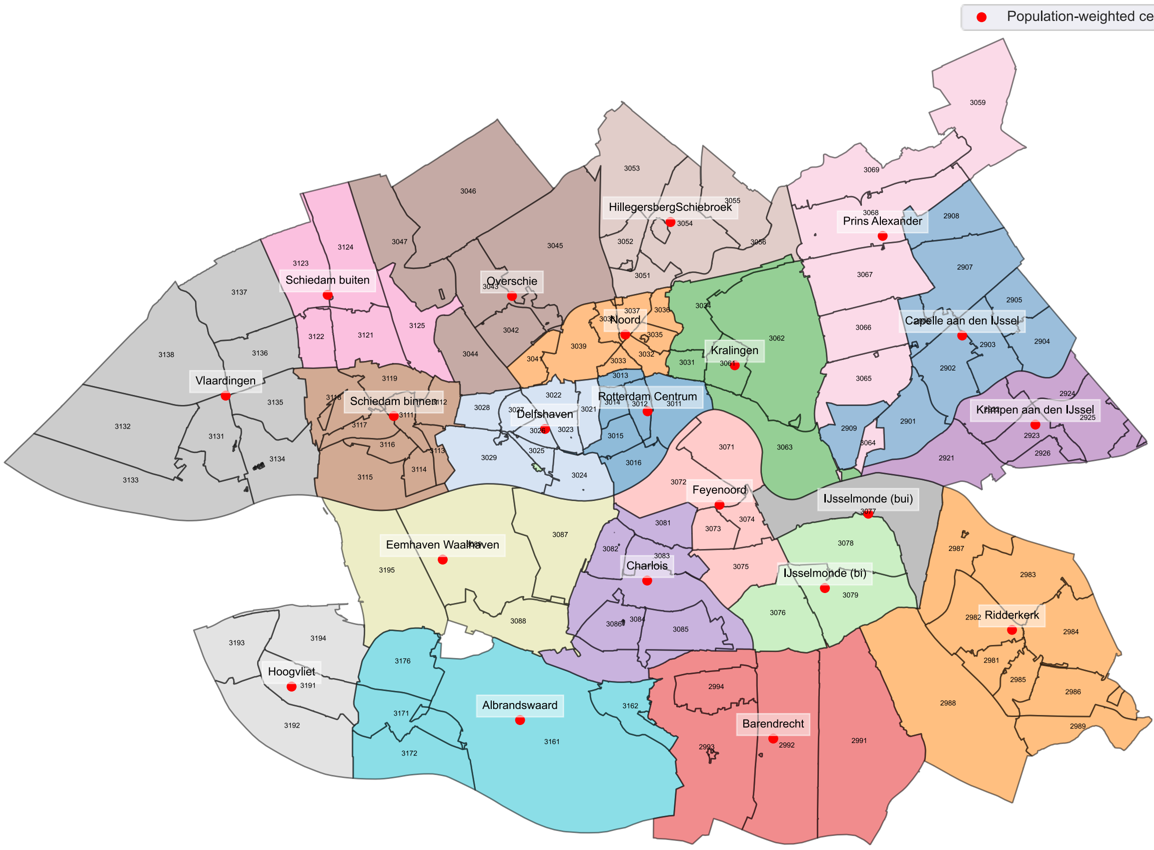


Fig 3.1: The main study area, divided into 21 MRDH regions and 125 postal code areas

Temporal structure

Temporally, simulations typically run from 05:00 to 24:00 with 5-minute time steps. This temporal scope was chosen to capture both peak and off-peak travel patterns, covering all significant periods of travel activity (the excluded overnight period accounts for less than 1% of daily trips according to ODiN data). Furthermore, it gives the traffic network time to ramp up to peak congestion and recover afterwards, and allow for stabilization of traffic patterns between peak periods.

The model uses discrete event simulation to activate agents with high temporal precision even if they are only activated a few times (3.5 on average) over a full day. A multi-scale temporal structure allows each component to have the temporal resolution it needs. While the overall system state is synced in 5-minute intervals, individual agents can initiate trips at any point in continuous time, derived from ODiN-based hourly probabilities distributed uniformly over that hour. The traffic simulation operates at several nested frequencies: vehicle platoons (representing 10 vehicles each, by default) are updated every 10 seconds for position and speed calculations, route choices are recomputed every 150 seconds (2.5 minutes) through Dynamic User Equilibrium (DUO), and network-wide metrics are collected at 15-minute intervals. Each of those temporal resolutions was determined comparing the performance-accuracy tradeoff, until a good balance was found between numerical accuracy and computational speed. The discrete event framework ensures that traveling agents complete their journeys regardless of system time steps, providing realistic travel times and allowing for natural emergence of peak spreading and congestion patterns.

Extensibility

While these parameters were used in the model implementation, it's worth noting that most source data is available for the entire Netherlands. The scripts to generate the OpenStreetMap network are designed to work with any urban area, and population data is available nationwide at the postal code level. The only data currently limiting the spatial scope are the origin-destination matrices from the V-MRDH model, which provide sufficient resolution only for the Rotterdam metropolitan region. Similarly, while this study focuses on single-day simulations, the model structure could accommodate multi-day runs, as trip probability data is available for every day of the week. This extensibility ensures that the modeling framework could be adapted for other cities or longer time periods in future research.

3.2 Key submodels

The model consists of two main submodels: the agent mode-choice model and the traffic simulation model. These submodels interact through agent decisions, which influence traffic flow and congestion patterns, which in turn affect mode choices of future agents. Various input data are entered into the submodels, which can be seen as a third submodel in itself. The conceptual model in Fig. 3.2 illustrates the key variables and interactions between submodels.

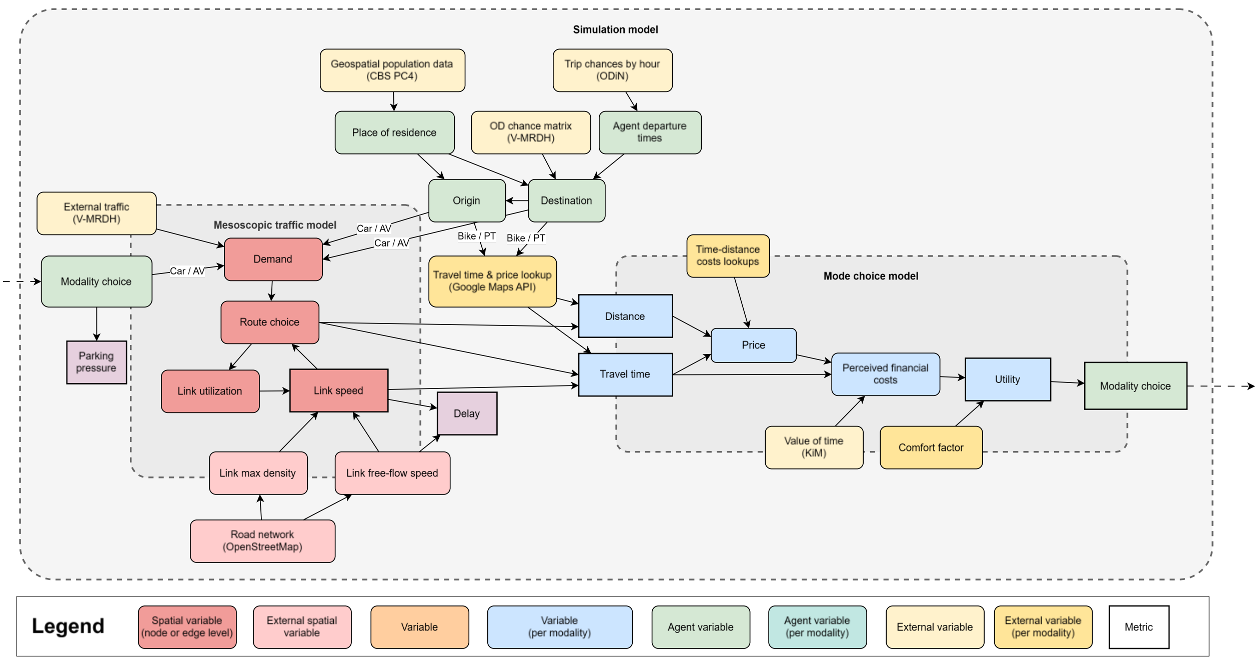


Fig 3.2: Conceptual model displaying the submodels, variables and their interactions

The model's submodels interact through a series of information flows and feedback loops, as illustrated in Figure 3.2. At its core, the model combines individual travel decisions with system-level traffic dynamics.

The process begins with input data feeding into both agent behavior and traffic simulation. Population data and trip patterns determine where and when agents travel, while the road network provides the physical infrastructure for the traffic simulation. For each potential journey, the agent first determines possible origins and destinations from empirical OD matrices, then evaluates available transport modes using a utility-based choice model.

When agents choose conventional cars or AVs, their trips feed into the mesoscopic traffic simulation as vehicle demand. The traffic simulation then calculates network conditions including congestion, delays, and travel times, which feed back into agents' future mode choices through updated travel times. For non-motorized modes (bicycle) and public transit, travel times remain fixed based on Google Maps API data, as these modes are assumed to be largely unaffected by congestion.

This creates two main feedback loops: a direct loop where traffic conditions influence immediate mode choices, and an indirect loop where accumulated trips affect network performance over time.

External factors like population distribution, mode-specific costs, and value of time heterogeneity influence these dynamics but remain constant during each simulation run. This allows the model to explore how different scenarios and policies might affect the complex interactions between individual travel choices and system-level transportation performance.

Input data

To enable realistic simulation of both individual travel decisions and emergent system-level effects, the model integrates multiple empirical data sources that inform agent behavior and validate aggregate outcomes.

Population and vehicle data

Population distribution and vehicle ownership data from CBS (2023) were used at the 4-digit postal code (PC4) level, representing approximately one million residents across 125 postal code areas. Car ownership varies significantly by area (19-65%, averaging 31.5%), enabling heterogeneous mode availability among agents.

Travel times and costs

Data for non-car modes was collected using the Google Maps Distance Matrix API for all 15,500 possible origin-destination pairs between postal codes, captured on a typical Thursday morning (2024-09-17, 08:00). For cars, travel times are calculated dynamically by the traffic simulation based on network conditions. Travel costs were derived from multiple sources:

- Car: Variable costs of €0.268/km based on Nibud data (Nibud-car-costs).
- Public Transit: Distance-based pricing following NS tariff structure (€0.169/km base rate, with declining rates for longer distances above 40 km, which turned out to not be present in the final simulation area).
- Bicycle: Assumed zero marginal cost.
- Autonomous Vehicles: Base fare €3.79 plus €1.41/km and €0.40/min, derived from Waymo pricing analysis as of September 2024 in Los Angeles (Waymo-pricing).

Road network

The network was extracted from OpenStreetMap (September 2024) and processed to include a detailed inner-city network with all roads from tertiary level upward, and a simplified surrounding network with major roads only. The complete network consists of 1,575 nodes and 3,328 edges, including attributes like speed limits, number of lanes, and road types. Roads under construction, including the new A16 motorway and Blankenburg tunnel, were included to represent near-future conditions.

Trip generation and distribution

Temporal trip patterns were derived from the Dutch National Travel Survey (ODiN 2023). The data shows a distinct sharp morning peak between 8 and 9 o'clock, and a little more spread out evening peak between 16 and 18 o'clock on weekdays. These patterns were used to create hourly trip generation probabilities for agents, to ensure agents start their trips at representative times.

Trip distribution

V-MRDH transport model for spatial distribution, which provides origin-destination matrices for different time periods (morning peak, evening peak, and off-peak). These matrices were processed to create probability distributions for trip destinations given each origin based on all transportation modes combined, so that the mode choice could be modelled internally as an agent decision rather than using mode-specific matrices.

Value of Time

Base values from KiM (2023) were used:

- Car: €10.42/hour
- Bicycle: €10.39/hour
- Public Transit: €7.12/hour
- AV: Scaled from car value using an adjustable factor (explored in scenarios)

Individual variation was introduced by applying agent-specific factors drawn from a lognormal distribution (mean 1.0, standard deviation 0.5, capped at 4.0), reflecting heterogeneous time valuations while maintaining reasonable bounds.

Section 6 of Appendix A provides more details on the input data sources, processing steps and motivation behind certain choices.

Agent behavior

Agents represent individual travelers with heterogeneous characteristics including home location, car ownership, possession of driver's license, and value of time (drawn from a lognormal distribution). Each agent generates a set of trips based on empirically-derived hourly probabilities, with destinations chosen according to origin-destination matrices from the V-MRDH model.

The model implements an agent-based version of the traditional four-step transportation demand model (McNally, 2007), adapting it for individual-level mode choice decision making while maintaining validated travel patterns. The first two steps (trip generation and distribution) are externally modelled based on empirical data, while the latter two steps (mode choice and route assignment) are modeled internally through agent behavior and traffic simulation. The four steps are implemented as follows:

Firstly, trip generation relies on hourly probabilities derived from ODiN 2023 data, with agents generating trips through *`generate_trip_times()`*.

Secondly, trip distribution assigns destinations using origin-destination probability matrices from the V-MRDH model through *`time_to_od_dict()`*. The matrices vary by time period (morning peak, evening peak, off-peak) to capture different travel patterns throughout the day.

Third, mode choice is implemented in `choice_rational_vot()`, where agents choose between available modes (conventional car, autonomous vehicle, bicycle, public transit) based on a rational choice model that minimizes comfort-adjusted perceived costs:

The perceived cost $C_{p,m}$ for a trip using mode m is calculated as:

$$C_{p,m} = \left(C_{m,m} + T_m \cdot V_m\right) \cdot \alpha_m$$

where:

- $C_{p,m}$ is the perceived cost for mode m
- $C_{m,m}$ is the monetary cost for mode m
- T_m is the travel time for mode m
- V_m is the value of time for mode m
- α_m is the comfort factor for mode m

Finally, route assignment for car and AV trips is handled by the UXsim traffic simulation. Other modes use fixed routes from Google Maps API data, which don't need to be modeled explicitly.

Trip chains are implemented as simple two-leg journeys (outbound and return), with mode availability constrained by previous choices (e.g., if departing by car, the return trip must also be by car).

Traffic Simulation

The traffic simulation component uses UXsim, a mesoscopic traffic simulator that implements a version of Newell's simplified car-following model. This model represents traffic flow as a kinematic wave, a balance between microscopic (individual vehicle) and macroscopic (flow-based) modeling. This approach provides computational efficiency while maintaining sufficient detail to model traffic dynamics and measure congestion at both link and area levels.

When agents choose car or AV as their travel mode, they are added to the traffic simulation as vehicles. For computational efficiency, vehicles are grouped into platoons of 10 vehicles, approximating the behavior of the actual 991,575 residents with about 100,000 agents. Each vehicle's driving behavior in a link is expressed as:

$$X(t + \Delta t, n) = \min\{X(t, n) + u\Delta t, X(t + \Delta t - \tau\Delta n, n - \Delta n) - \delta\Delta n\}$$

where $X(t, n)$ denotes the position of platoon n at time t, Δt denotes the simulation time step width, u denotes free-flow speed of the link, and δ denotes jam spacing of the link. This equation represents vehicles traveling at free-flow speed when unconstrained, while maintaining safe following distances when in congestion.

Traffic behavior at intersections is handled by the incremental node model, which resolves conflicts between competing flows by processing vehicles sequentially based on predefined merge priorities. This approach maintains consistency with the kinematic wave model while efficiently managing complex intersection dynamics. Since OpenStreetMap data lacked explicit intersection information, merge priorities were set to default values, giving each incoming lane equal priority.

For route choice, UXsim employs a [Dynamic User Optimum](#) (DUO) model with stochasticity and delay. The attractiveness $B_o^{z,i}$ of link o for vehicles with destination z at time step i is updated as:

$$B_o^{z,i} = (1 - \lambda) B_o^{z,i-\Delta i_B} + \lambda b_o^{z,i}$$

where λ is a weight parameter and $b_o^{z,i}$ indicates whether link o is on the shortest path to destination z. This formulation allows vehicles to gradually adapt their routes based on evolving traffic conditions, rather than instantly responding to changes in travel times.

Road characteristics are differentiated by road type, with motorways having lower jam densities (0.14 vehicles/meter/lane) than local streets (0.20 vehicles/meter/lane).

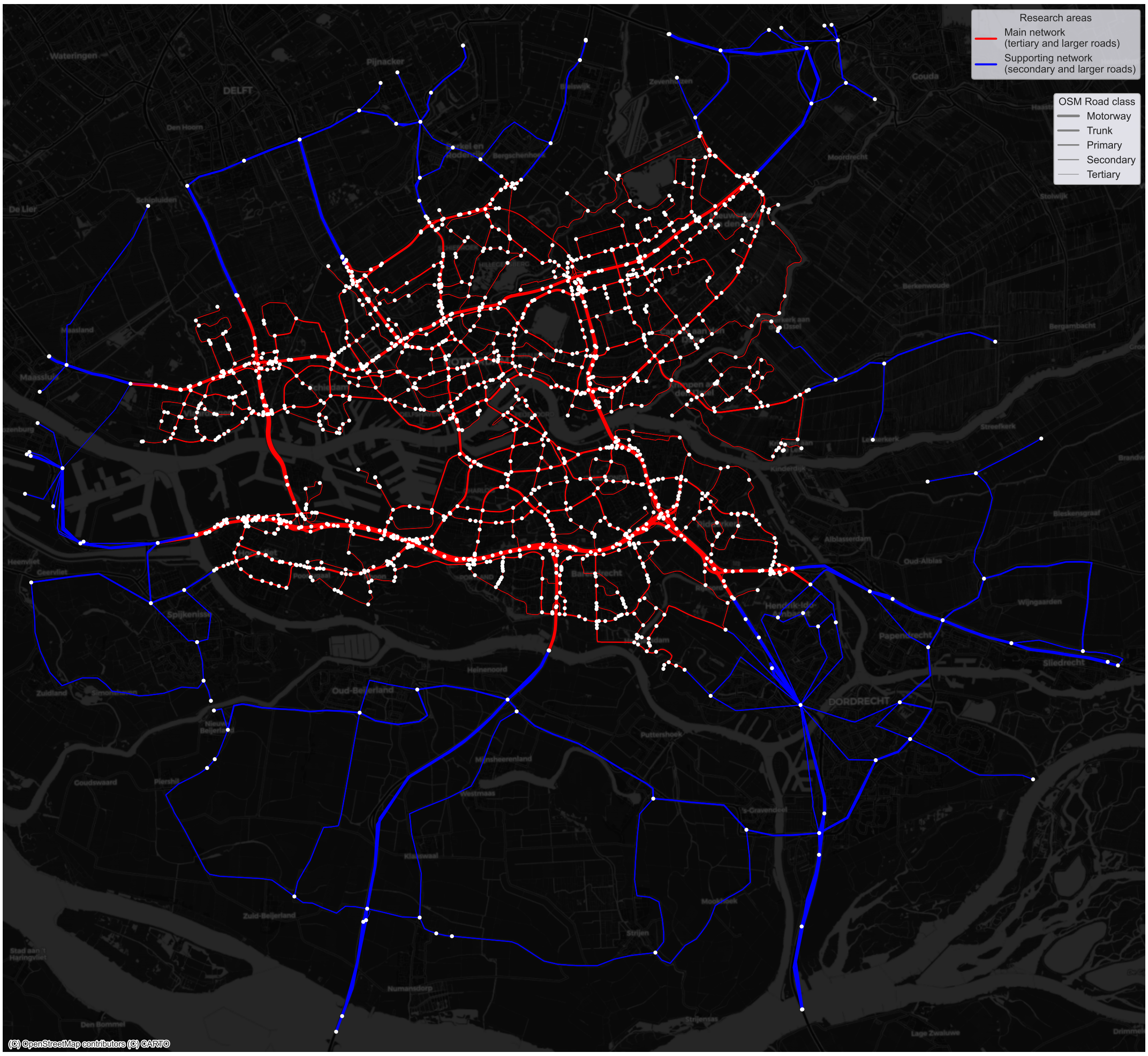


Fig 3.3: The road network used in the traffic simulation

3.3 Model interaction and behavior

The model contains several important interaction patterns and feedback loops that drive its behavior. Three key dynamics emerge as particularly significant: congestion-based stabilization, mode choice reinforcement, and spatial-temporal patterns.

Congestion-based stabilization

The primary stabilizing feedback loop operates through traffic congestion. When agents choose car or AV modes, they contribute to network traffic, which affects travel times through the kinematic wave model. These updated travel times then influence subsequent mode choices through the perceived cost calculation. This creates a negative feedback loop: as more agents choose motorized modes, congestion increases, leading to longer travel times and higher perceived costs, which makes these modes less attractive to subsequent agents. This mechanism helps prevent the system from reaching gridlock, though it can still occur in extreme scenarios (as seen in Section 5.2 with inefficient AVs).

Mode choice reinforcement

While congestion provides negative feedback, the model also contains positive feedback through trip chaining. Once an agent chooses a car for an outbound trip, they must use it for the return journey, as the vehicle needs to return home. This creates a form of path dependency where initial mode choices constrain future options, potentially amplifying the impact of factors that influence initial choices (like weather or time of day).

Spatial-temporal dynamics

The interaction between trip generation and network conditions creates distinct spatial-temporal patterns. While the ODiN-derived trip probabilities generate similar morning and evening peaks, the actual system behavior differs significantly. As shown in Section 3.5.2, the evening peak experiences more severe congestion than the morning peak, despite similar trip generation rates. This emergent behavior arises from the interaction between more dispersed evening destinations (versus concentrated morning commute patterns), accumulation of delay effects throughout the day, and trip chain constraints limiting mode-switching options.

Tipping point behavior

The model exhibits notable tipping points related to AV adoption and system performance. These emerge from the interaction between density-dependent congestion (varying by road type), heterogeneous value of time among agents (following a lognormal distribution), and mode-specific comfort factors. These mechanisms interact to create sharp transitions in system behavior. As shown in Section 5.1, when AV costs drop below certain thresholds, the system can rapidly shift from one stable state to another, particularly when AV density factors are favorable. This occurs because the initial adopters (those with high value of time) reduce congestion enough to make AVs attractive to additional users, creating a cascading effect.

Critical transitions

The model reveals potential critical transitions in urban mobility patterns, particularly around AV adoption thresholds. Three distinct system states become apparent:

1. **Car-dominated equilibrium**: With expensive AVs, the system maintains a stable mix of modes similar to current patterns.
2. **Mixed transition state**: As AV costs decrease, the system enters a less stable state with shifting mode shares.
3. **AV-dominated state**: With very cheap AVs and favorable density factors, the system can tip into a new equilibrium with high AV usage.

These transitions are particularly interesting because they depend on multiple interacting factors. The tipping points are not determined by any single variable but emerge from the interaction between costs, perceived time value, vehicle density, and the underlying feedback loops in the system.

These interaction patterns and emergent behaviors help explain many of the results observed in Sections 5 and 6, particularly the non-linear responses to policy interventions and the existence of distinct future scenarios depending on AV characteristics. The combination of stabilizing feedback through congestion, reinforcing feedback through trip chains, and tipping point dynamics through heterogeneous adoption creates a rich system behavior that can't be predicted from individual components alone.

3.4 Limitations

The model has important limitations that should be considered when interpreting its results. Three major limitations are highlighted in this section, as well as several minor limitations that may affect specific aspects of the model. The distinction is made by what effect we expect the limitation to have on the results: major limitations are expected to have a significant impact on the model's ability to accurately represent reality, while minor limitations are expected to have a more limited impact, as least in the specific scope and goal of this research.

Appendix C: Limitations provides a comprehensive overview of all limitations, including their potential impact on the model.

Major limitations

The primary limitation is its temporal scope - the model simulates only a single day and does not capture long-term effects such as land use changes, vehicle ownership decisions, or evolving destination patterns. While this allows for detailed analysis of immediate system responses to AV introduction, it may miss important feedback loops that develop over longer timeframes.

A second key limitation lies in the travel demand model's static nature. Unlike activity-based approaches, the model does not account for how the availability of AVs might fundamentally alter trip timing, destination choices, or activity patterns. Trip generation and distribution are based on current travel patterns, which may not accurately reflect behavior in a future with widespread AV adoption.

The mode choice model represents a third major limitation, implementing a simplified rational choice framework that may not fully capture the complexity of real-world travel decisions. While heterogeneity is introduced through varying values of time, the model does not account for habitual behavior, psychological factors, or complex preferences beyond a single comfort factor per mode. This could lead to more extreme or more gradual modal shifts than might occur in reality.

Minor limitations

There are several smaller limitations. Regarding agent behavior and interactions, the model lacks several important behavioral mechanisms. Agents do not learn from or adapt their behavior based on previous experiences, such as experienced travel times or costs. There are no direct agent-to-agent interactions, meaning social influence processes and informal arrangements like household car sharing are not captured. The model also simplifies mode choice to just four options (car, bike, AV, transit), omitting potentially important alternatives like walking or e-scooters. Additionally, while parking occupancy is tracked, parking availability and search time are not dynamically modeled into mode choice decisions, which could underestimate the full costs of car-based travel in dense urban areas.

The representation of transportation infrastructure and networks presents another set of limitations. The traffic simulation does not explicitly model traffic signals, intersection priorities, or detailed merging behaviors, which may affect the accuracy of congestion patterns particularly in dense urban areas. Public transit is represented through fixed travel times rather than explicit schedules and routes, preventing the model from capturing capacity constraints or service frequency effects. Similarly, bicycle and transit routes are based on travel times from a single Thursday morning, not accounting for variations throughout the day or week that might influence mode choice.

External factors that could significantly impact travel behavior are also simplified or omitted. The model does not account for weather conditions, seasonal variations, or incidents that could affect both mode choice and traffic patterns. External traffic entering and leaving the study area is implemented through fixed origin-destination matrices with simple time-of-day factors, not responding dynamically to changing conditions within the model. Furthermore, the underlying origin-destination matrices from the V-MRDH model are at a relatively coarse spatial resolution, potentially missing important local variations in travel patterns, especially for shorter trips.

3.5 Default behavior

The default behavior of the model represents the current situation in Rotterdam without autonomous vehicles. This scenario serves as a reference point for comparing the effects of AV adoption and policy interventions, and serves as validation for the model’s ability to reproduce existing travel patterns.

3.5.1 Mode choice

Mode choice is the main decision-making process for agents in the model. Figure 3.4 shows the mode distribution of modes throughout the day, showing how agents choose between car, bicycle and public transit without AVs being present.

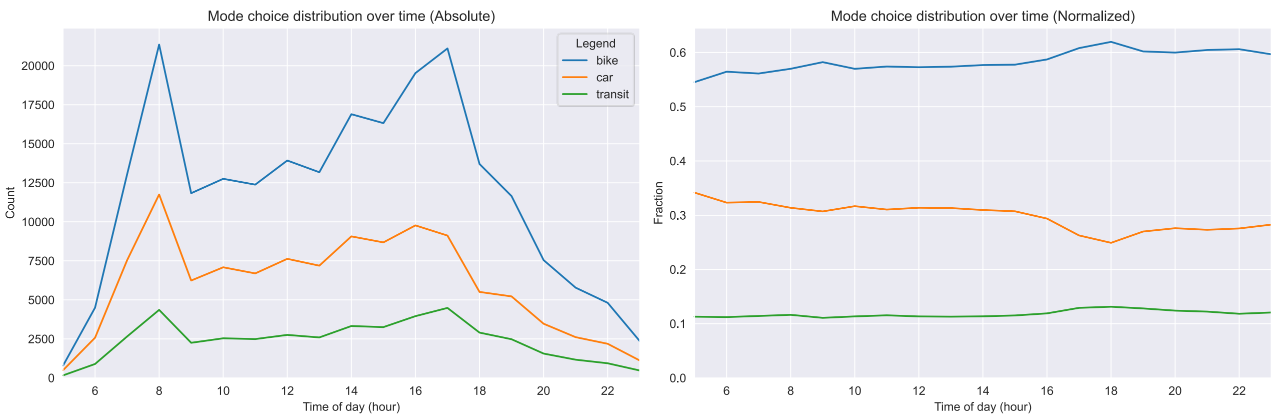


Fig 3.4: Mode distribution of all trips in the default scenario

The absolute trip distribution shows two clear peaks in travel demand: a sharp morning peak around 8:00 and a broader evening peak between 16:00-18:00, consistent with the input distribution from the ODiN data. During these peak periods, all modes see increased usage, though their relative proportions remain fairly stable.

Looking at peak hours, suggesting that congestion may be a factor in mode choice, but the effect is relatively minor compared to the overall distribution. the normalized mode shares, cycling is consistently the dominant mode, accounting for 55-60% of all trips throughout the day. Car usage represents about 25-35% of trips, showing slight variations during peak hours, while public transit maintains a relatively stable share of 10-15%. Car usage does decrease slightly during the day, and especially during the evening rush hours, and recovers slightly in the evening. The stability of these proportions throughout the day suggests that while the absolute number of trips varies significantly, the relative attractiveness of different modes remains consistent.

3.5.2 Trip distributions

Details about each trip show how travel times, distances, costs, and perceived costs are distributed across different modes in the default scenario. Figure 3.5 displays the distributions of these metrics for all trips in the default scenario.

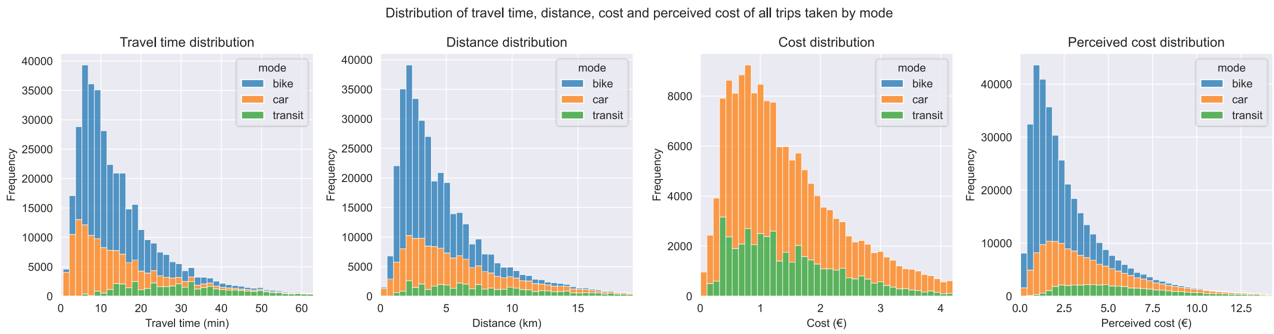


Fig 3.5: Trip distributions for all trips in the default scenario

The travel time distribution shows the bike to be the dominant mode for most short trips, under 20 minutes. Cars do have a significant share of trips in this region, but also extend further. Transit is almost not used for trips under 10 minutes, which is expected as public transit is generally not suited for very short trips.

In terms of distance, most bicycle trips are concentrated in the 1-5 km range, while car trips show a more gradual distribution extending into the longer distances. Transit journeys have a flatter distribution, suggesting it's chosen more often for longer trips.

Notable is that cars take up the majority of the very short trips, which is an artifact of the model implementation: Bike and public transit goes from 4-digit postal code (PC4) centroid to PC4 centroid, while cars can go from any road node to any road node, which includes the shortest trips. While this skews the data slightly, it does not affect the overall mode shares since it averages out over all travel time and distances.

The cost distribution reflects the model's assumptions about mode costs: bicycle trips incur no monetary costs, car costs show a roughly log-normal distribution, and transit costs display similar pattern. These monetary costs combine with time costs to create the perceived cost distribution, where car journeys show the highest total costs despite often having shorter travel times than transit.

Finally, all metrics follow a similar log-normal distribution, with a long tail of high values. This is consistent with the ODiN data on actual travel patterns and logical since the V-MRDH model is calibrated on ODiN, among others. Also note how the perceived costs distribution is perfectly smooth, which is a nice confirmation that agent's indeed correctly make decisions to minimize their perceived costs, and the comfort-factor doesn't add too much noise besides skewing the distribution in favor of cars and against bicycles.

3.5.3 Network metrics

The network-level metrics show how traffic, congestion and delays are distributed throughout the day in the default scenario. Figure 3.6 displays the total traffic volume, average speed, delay factor, and vehicle density across the road network.

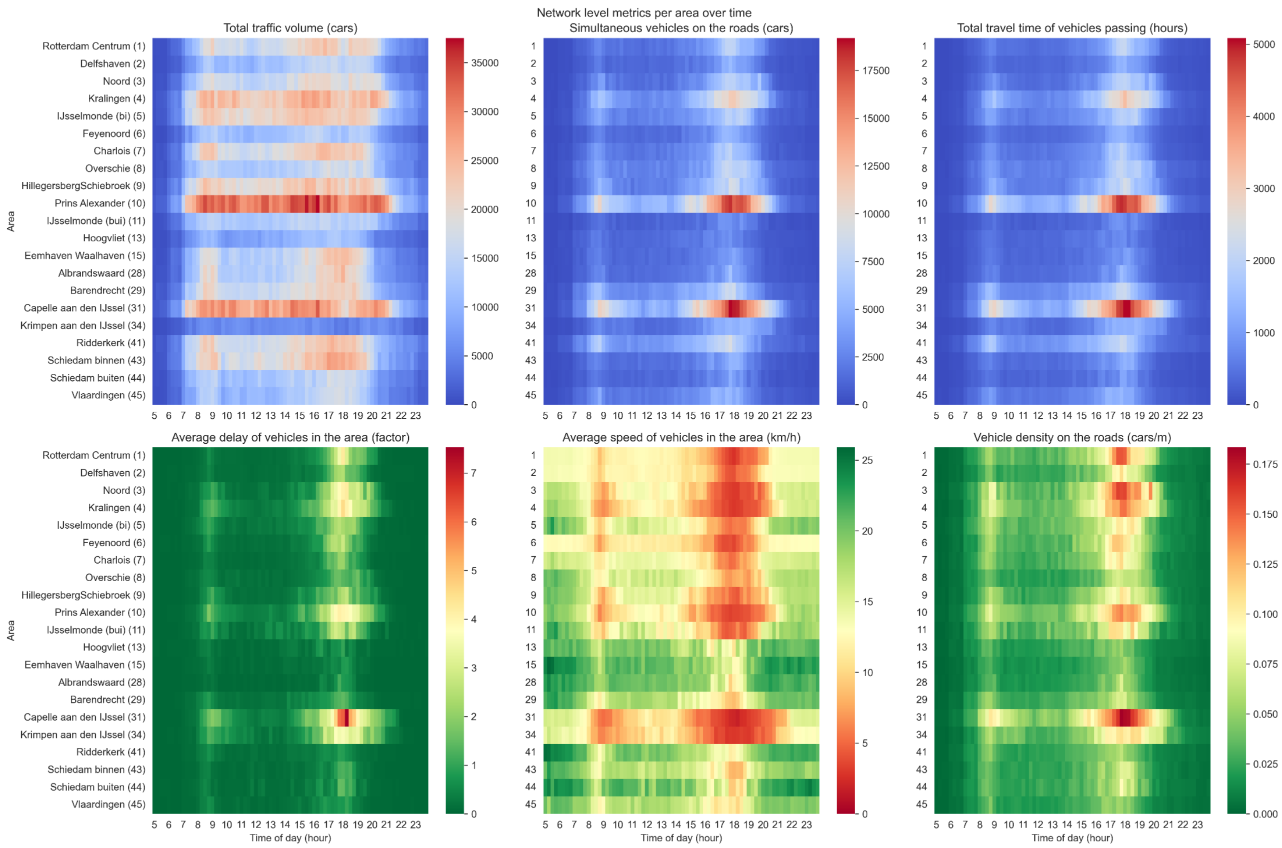


Fig 3.6: Network metrics for all trips in the default scenario

The total traffic volume exhibits clear morning and evening peaks, with particularly high volumes in Prins Alexander (10) and Capelle aan den IJssel (31). These areas experience significantly higher traffic volumes than other regions. These extreme values are likely due to a combination of high car ownership rates (see Fig A.2 in Appendix A.6 input data), substantial external traffic from surrounding municipalities (see Fig A.13), and ongoing major infrastructure projects around the Terbregseplein interchange and new A16 motorway construction.

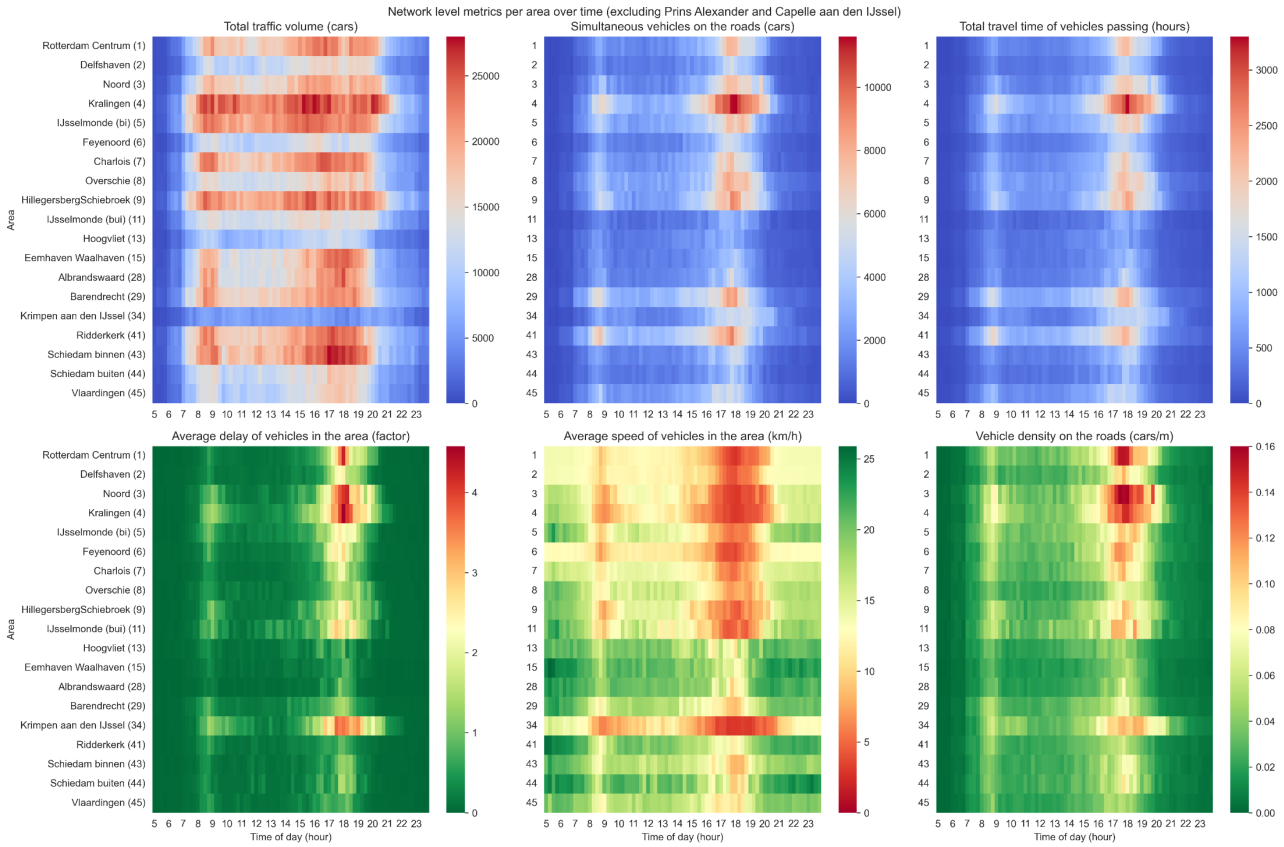


Fig 3.7: Network metrics for all trips in the default scenario (without outlier regions Prins Alexander (10) and Capelle aan den IJssel (31))

To better observe patterns in other regions, Figure 3.7 excludes these outlier areas. In the inner-city areas, particularly Rotterdam Centrum (1), Noord (3), and Kralingen (4), show moderate but consistent traffic volumes throughout the day. Average speeds in these areas remain relatively low (10-15 km/h) compared to outer regions (20-25 km/h), with the average speed dropping below 10 km/h briefly in the morning peak and for longer periods during the evening peak, with very high vehicle densities, especially in the evening peak.

The delay factor (actual travel time divided by free-flow travel time) shows that in these three inner-city areas, delays are consistently high during the evening peak, with journeys taking up to times the free-flow travel time. This suggests that congestion is a significant issue in these areas, particularly during peak hours. Krimpen aan den IJssel (34) is another notable outlier, which is notoriously limited by the Algera bridge, which is a major bottleneck in the area (oeververbindingen.nl, capellebouwtaandestad.nl). Some of the traffic towards the Algera bridge piles up in Capelle aan den IJssel (31), which could help explain the high traffic volumes and delays in that area.

These metrics demonstrate that while the transportation network functions efficiently during most hours, certain areas - particularly the inner city of those limited by natural barriers - experience significant congestion and delays during peak periods. It's great to observe that the model captures complex traffic behavior relatively well, like a short morning peak, extensive evening peak, and specific congestion points.

3.6 Validation

The validation of complex agent-based models requires evaluating multiple aspects of model behavior against empirical data and theoretical expectations. Rather than seeking absolute accuracy, validation focuses on determining whether the model can meaningfully address its intended research questions. This section examines the model's validity through four key aspects: mode choice distribution, travel patterns, network behavior, and systematic validation procedures, building on the behavior observed in sections 3.3 and 3.5. For each aspect, we compare model behavior against available empirical data, identify limitations, and assess implications for the model's ability to examine AV adoption effects. The validation results suggest the model captures key urban mobility dynamics adequately for exploring system-level changes, while specific numerical predictions should be interpreted with appropriate caution.

Mode choice validation

The model's default behavior was validated against ODiN 2023 data for the Rotterdam area. In the inner city (Noord, Kralingen, Rotterdam Centrum, Feyenoord, Delfshaven), the model produces mode shares of 11.3% car, 82.3% bicycle, and 6.5% transit, compared to empirical values of 13.4%, 69.9%, and 16.7% respectively. For the broader study area, the model shows 25.4% car, 65.1% bicycle, and 9.5% transit usage, versus empirical values of 37.7%, 49.0%, and 13.3%.

While the model shows some deviation from empirical data, particularly overestimating bicycle usage and underestimating car use, these differences are consistent with the model's focus on short to medium-term effects. The model doesn't capture certain car-favoring factors like weather, cargo requirements, and multi-stop trips, which likely explains the lower car mode share. However, the relative order of mode preferences and general patterns align with observed behavior, suggesting sufficient validity for examining modal shifts.

Travel pattern validation

Temporal travel patterns show strong alignment with empirical data, particularly in capturing peak hour characteristics. The model reproduces the sharp morning peak (8:00-9:00) and broader evening peak (16:00-18:00) observed in ODiN data, both in terms of timing and relative magnitude. This validation is particularly important as these temporal patterns drive the emergence of congestion and system-level effects.

Trip distance distributions follow expected log-normal patterns, with bicycles dominating shorter trips (1-5 km) and motorized modes becoming more prevalent at longer distances, consistent with ODiN data. The distance distributions for each mode also align with the V-MRDH model's origin-destination patterns, providing additional confidence in the spatial distribution of trips.

The journey duration distributions show plausible relationships between modes, with bicycles being most competitive for trips under 20 minutes and transit becoming more prevalent for longer journeys. While direct validation of travel times against measured data was not possible, the relative differences between modes and the overall patterns align with expectations from urban transportation theory and observed behavior in similar cities.

Network behavior validation

The traffic simulation component demonstrates plausible behavior in several key aspects. Known congestion points, such as the Algera bridge bottleneck in Krimpen aan den IJssel and the Terbregseplein interchange, show appropriate congestion patterns. The model captures expected phenomena like longer delays during evening peaks compared to morning peaks, and higher congestion in dense urban areas versus peripheral regions.

Network speeds in the default scenario average 25 km/h, decreasing to 10-15 km/h in congested inner-city areas during peak hours, which aligns with typical urban traffic patterns. While precise validation against measured traffic data was not possible due to data availability constraints (commercial entities not willing to share data), these patterns are consistent with general urban traffic behavior and sufficient for examining relative changes under different scenarios.

Suitability for research questions

The model's components can be evaluated against the requirements for answering each research question:

For subquestion A (how to represent tradeoffs and effects), the model combines validated mode choice behavior with traffic simulation at appropriate scales. While not perfect, the validated mode shares and travel patterns indicate the model captures important aspects of urban mobility decisions, and the network behavior shows plausible congestion and feedback effects. The modular design enables exploration of different effects by modifying individual components.

For subquestion B (AV adoption under uncertainties), the model provides a validated representation of current travel behavior as a baseline, with explicit parameterization of key AV characteristics (cost, value of time, density). While AV-specific behavior cannot be validated due to its future nature, the model's representation of existing mode choice mechanisms offers a reasonable foundation for exploring potential responses to this new option. The heterogeneous value of time implementation helps capture varying adoption patterns, though actual adoption behavior may differ.

For subquestion C (system effects), the model's network behavior shows key expected characteristics. The reproduction of known congestion patterns, peak hour dynamics, and area-specific traffic flows suggests the model can represent relevant system-level effects. The geographic (125 postal codes) and temporal (5-minute) resolution allows examination of both local and system-wide impacts, though some local effects may be oversimplified.

For subquestion D (policy effectiveness), the model combines plausible travel behavior with network responses, enabling evaluation of policy interventions. The representation of different urban areas and travel patterns allows assessment of spatially and temporally targeted policies. However, the model necessarily simplifies policy implementation details and may not capture all behavioral responses to interventions.

In summary, while the model has clear limitations, its components align with key aspects needed to explore the research questions. Like in most simulation studies exploring human behavior and uncertainties, focus on relative changes rather than absolute predictions should be the focus, making the model a useful, if imperfect, tool for examining potential impacts of autonomous vehicles on urban transportation systems.

4. Experimental design

Two main experiments were conducted to explore the potential impacts of autonomous vehicles and evaluate policy interventions: a scenario analysis investigating uncertainties in AV adoption and its effects, to answer subquestion B (looking at mode shares) and C (looking at high-level KPIs), and a policy analysis testing interventions across selected scenarios, to answer subquestion D.

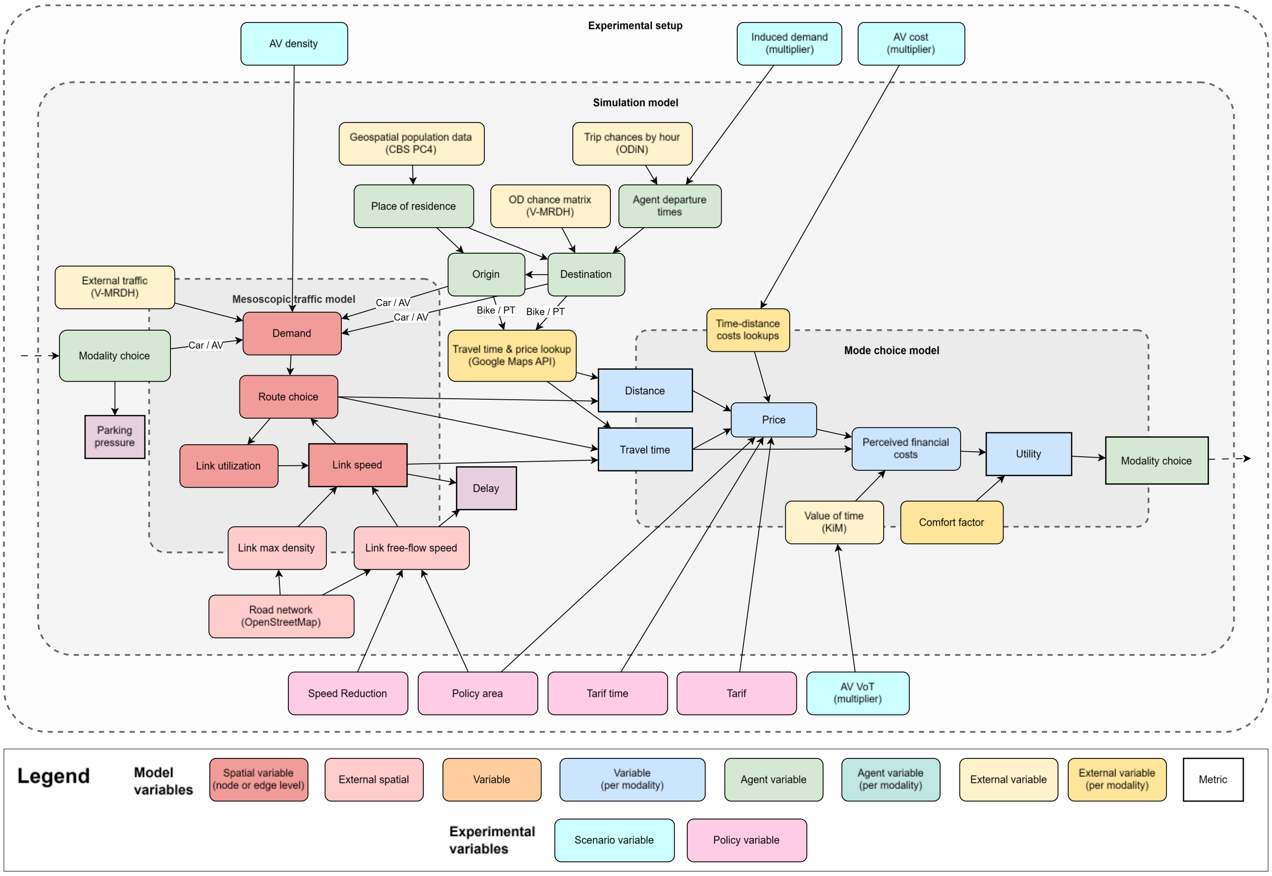


Fig 4.1: Conceptual model including scenario uncertainties and policy levers

Figure 4.1 shows how the scenario and policy variables will influence the system. The scenario variables will influence the number of AV cars generated, the frequency with which travelers plan trips, the AV costs and the travelers value of time when using an AV. The policy variables will influence the AV price and the maximum allowed speeds.

4.1 Scenario analysis

To answer subquestions B and C, a systematic exploration of key uncertainties was needed. A full-factorial design was chosen over alternatives like Monte Carlo or Latin Hypercube sampling for several reasons. First, factorial designs enable systematic exploration of interactions between variables while maintaining interpretability - each scenario represents a clear combination of parameter values that can be directly compared to others. Second, the logarithmic spacing of certain variables (particularly costs) allows exploration of non-linear effects that might be missed with uniform sampling. Third, the relatively small number of levels per variable (3-4) made a full factorial computationally feasible while still capturing the variations of interest. Future research may expand on this by either exploring interesting areas in this space in higher resolution (to find thresholds) or outside it (to explore extreme value scenarios).

The scenario analysis explored four key uncertainties:

1. AV Cost Factor (4 levels: 1.0, 0.5, 0.25, 0.125)
    - Relative cost of using AVs compared to current Waymo prices
2. AV Value of Time Factor (3 levels: 1.0, 0.5, 0.25)
    - Perceived value of time spent in AVs versus conventional vehicles
3. AV Density (4 levels: 1.5, 1.0, 0.5, 0.333)
    - Space efficiency of AVs relative to conventional vehicles
4. Induced Demand (3 levels: 1.0, 1.25, 1.5)
    - Potential increase in overall travel demand

The AV cost factor spans from current prices to one-eighth of current costs, with values decreasing by a factor of two at each step. This logarithmic spacing reflects the expectation that cost differences matter more at lower price points, where they might trigger significant changes in adoption patterns. The current prices are based on Waymo's pricing in Los Angeles as of September 2024, providing a real-world baseline for comparison.

The value of time factor explores how users might perceive time spent in AVs differently from conventional vehicles. A factor of 1.0 represents equivalent time value to current cars, while lower values (0.5 and 0.25) represent scenarios where time in AVs is perceived as less costly, due to the ability to work, rest, or engage in other activities.

AV density represents how efficiently autonomous vehicles might utilize road space, measured as the relative space required per person transported compared to current vehicles. Values above 1.0 indicate less efficient operation (due to increased safety margins or lower occupancy), while values below 1.0 represent improved efficiency. This efficiency could be achieved through various mechanisms: higher occupancy from better ride-matching, reduced following distances through platooning or faster reaction times, smaller vehicles optimized for urban trips, or combinations thereof. For instance, a density factor of 0.5 might represent either doubled average occupancy, halved following distances, or a mix of improvements. The range spans from 1.5 (cautious operation, increased empty trips) to 0.333 (high road efficiency, multi-person occupancy and/or few empty trips). By treating density as an outcome-based metric rather than specifying implementation details, the model remains relevant regardless of which solutions are used and will emerge.

Induced demand factors were chosen based on historical precedent from major transportation improvements, ranging from no increase (1.0) to a 50% increase (1.5) in trip generation. This range captures both conservative and aggressive estimates of how improved mobility might stimulate additional travel, and simultaneously how demand might grow in general due to external factors.

This design resulted in 144 unique combinations (4×3×4×3), each representing a possible future scenario. Each scenario was simulated for a full day (19 hours) with consistent base parameters including road network configuration, population distribution, and external traffic patterns.

4.2 Policy analysis

To answer subquestion D, eight representative scenarios were selected from the scenario analysis results, ranging from "current situation" to "extreme progress" in AV adoption:

Scenario	*AV cost*	*AV density*	*Induced demand*
Current situation	1.0	1.5	1.0
Moderate progress	0.5	1.0	1.125
Extensive progress	0.25	0.5	1.25
Extreme progress	0.125	0.333	1.5
Private race to bottom	0.125	1.5	1.25
Mixed race to bottom	0.125	1.0	1.25
Shared race to bottom	0.125	0.5	1.25
Dense progress	0.25	0.333	1.125

Table 4.1: Overview of selected scenarios for policy analysis

These scenarios were chosen to span the range of plausible futures identified in the scenario analysis, with particular attention to cases that showed interesting or concerning system-level effects. The selection includes both optimistic scenarios where technological progress leads to efficient, affordable AVs, and more problematic scenarios where cheap but inefficient AVs could create new urban challenges.

These scenarios were tested against nine policy combinations:

Policy	*Area*	*Speed Reduction*	*Tariff (€)*	*Timing*
No policy	City	None	0	-
Autoluw peak	Autoluw	-20 km/h	5	Peak
Autoluw day	Autoluw	-20 km/h	5	Day
City peak	City	-20 km/h	5	Peak
City day	City	-20 km/h	5	Day
City speed only	City	-20 km/h	0	-
City peak tariff	City	None	5	Peak
City day tariff	City	None	5	Day
All out	City	-20 km/h	10	Day

Table 4.2: Overview of policy combinations for policy analysis

The policy combinations were designed to test both the individual and combined effects of two main intervention types: speed reductions and congestion pricing. Speed reductions of 20 km/h represent a significant but feasible change in urban speed limits, in line what cities as Amsterdam are doing by lowering speed limits from 50 km/h to 30 km/h. The pricing levels (€5 and €10) were chosen to be substantial enough to influence behavior while remaining within ranges seen in existing congestion pricing schemes, in line with congestion pricing in cities as New York, which $15 in peak hours and $3.75 off-peak.

Geographic targeting was included through two spatial scales: the "autoluw" area representing Rotterdam's central low-traffic zone (affecting about 13% of the population), and city-wide implementation covering all 125 postal code areas. Temporal variations were explored through peak-hour (7:00-9:00 and 16:00-18:00) versus all-day (6:00-19:00) implementation, the current definitions used in The Netherlands for peak hours and daytime.

This created 72 scenario-policy combinations (8×9), allowing examination of policy effectiveness under different future conditions. Each combination was evaluated using multiple metrics including mode shares, network performance, and total vehicle kilometers traveled, enabling analysis of both intended and unintended policy effects.

Both experiments used the same base model configuration, differing only in the manipulated variables. Results were collected on journey details (origin, destination, mode, costs), traffic conditions (speed, density, flow), and parking occupancy, enabling comprehensive analysis of system-level effects.

5. Results

This section presents the findings from two major experiments: a full-factorial analysis exploring 144 scenarios of AV adoption, and a focused policy analysis testing 72 combinations of scenarios and interventions. The results are organized in three parts that directly address our research subquestions.

First, Section 5.1 examines AV adoption patterns and modal shifts across different scenarios, answering subquestion B about how self-driving cars will be adopted under different uncertainties. Section 5.2 analyzes the system-level effects including congestion, network performance, and total vehicle kilometers traveled, addressing subquestion C about which urban problems are amplified or reduced by AVs. Both are based on the scenario analysis as described in section 4.1, but looking at different outcome metrics.

Finally, Section 5.3 evaluates the effectiveness of various policy interventions across different scenarios, answering subquestion D about which policies can effectively mitigate negative impacts while preserving benefits. This section is based on the policy analysis as described in section 4.2.

Section	*Subquestion*	*Experiment*	*Metrics*
5.1: AV adoption & modal shift	B	Scenario analysis	AV mode share, mode-distance share, modal shift patterns
5.2: System effects	C	Scenario analysis	Network performance, congestion levels, vehicle kilometers traveled, travel times
5.3: Policy effectiveness	D	Policy analysis	Mode shares, network performance, system-wide metrics

Table 5.1: Overview of which section answers which subquestion by which experiment examining which metrics

Interpreting the results

Many of the results will be displayed in dimensionally-stacked heatmaps. In each, one metric is displayed for all 144 scenarios. There are two x-axes and two y-axes, one for each of the 4 uncertainties from which the scenarios are derived:

- Inner (upper) x-axis: The AV Value of Time (VoT) factor, ranging from 1.0 to 0.25 (lower means less valuable).
- Outer (lower) x-axis: The AV Cost Factor, ranging from 1.0 to 0.125 (lower means cheaper).
- Inner (left) y-axis: Induced Demand factor, ranging from 1.0 to 1.5 (higher means more demand).
- Outer (right) y-axis: AV Density factor, ranging from 1.5 to 0.333 (lower means less space per person kilometer taken up).

Each value (tile) in the heatmap represents the metric value for the corresponding scenario. The structure and order is identical for all heatmaps, allowing for visual comparison of different metrics across the scenarios. Generally, outcomes preferred by (most) stakeholders are displayed in green, while undesired outcomes are displayed in red, with the reference scenario (no AVs) being the yellow midpoint. If the preferred direction of a metric is not clear, brown indicates low values and blue indicates high values, with white being the reference scenario.

5.1 AV adoption & modal shift

To understand how autonomous vehicles might be adopted in urban environments and their impact on existing transportation modes, we first analyze the uptake of AVs and resulting changes in mode shares across our scenario space. This will answer subquestion B, under which circumstances AVs are likely to be adopted and how they affect the use of other modes.

AV adoption

Fig 5.1 shows the mode share and mode-distance share of AVs in the 144 scenarios. The mode share represents the percentage of total trips made by AVs, while the mode-distance share represents the percentage of total distance traveled by AVs.

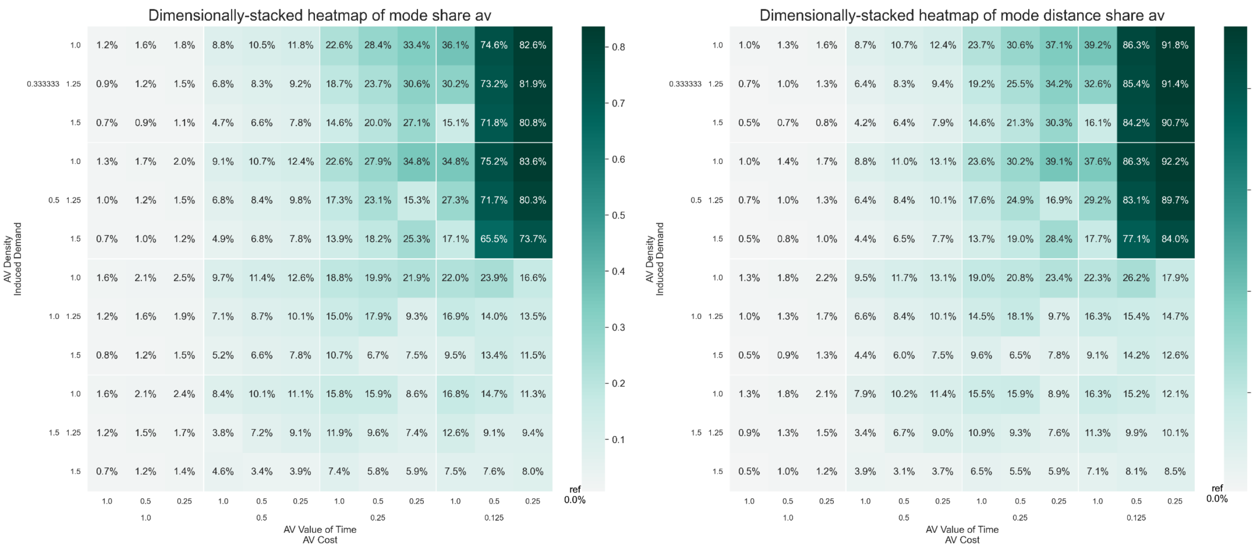


Fig 5.1: Mode share and mode-distance share of Avs in different scenarios

In the scenarios to close to current pricing, Avs are only marginally adopted, for between 0.7% and 1.6%. While this is between 25.000 to 60.000 daily trips, it's not significant in the total of 3.5 million daily trips in the area. The density factor plays a small but notable role here, with AV adoption being about half if total travel demand increases by 50%.

While the AV density and passenger's value of time have some effect on the adoption of Avs, reducing the costs is what really drives AV adoption. Halving the costs increases the adoption by more than 5x, floating between 5 and 12 percent. Halving it again leads to another major increase up to 33%, which is also the first time the AV density starts to play a significant role. A density of 0.5 or 0.333 leads to significantly higher adoption, which will be further explorer in section 5.2.

The AV distance share, which is the share of total distance traveled by AVs, shows very similar patters, being a slightly higher in the high-adoption scenarios.

Finally, with the price being reduced to one-eight (0.125) or the current costs, Avs are cheap enough to be massively adopted. However, this has two pre-requisites: the value of time has to be at most 0.5, and the density has to be at most 0.5. With an density of 1.0 or 1.5 or a value of time of 1.0, the adoption is still significant in the 15 to 35 percent ranges, but won't reach the massive 65%+ adoption that otherwise is reached.

Modal shift

Fig 5.2 shows the mode share of cars, bicycles, and public transit in the 144 scenarios, which allows us to see how the adoption of AVs affects the use of other modes.

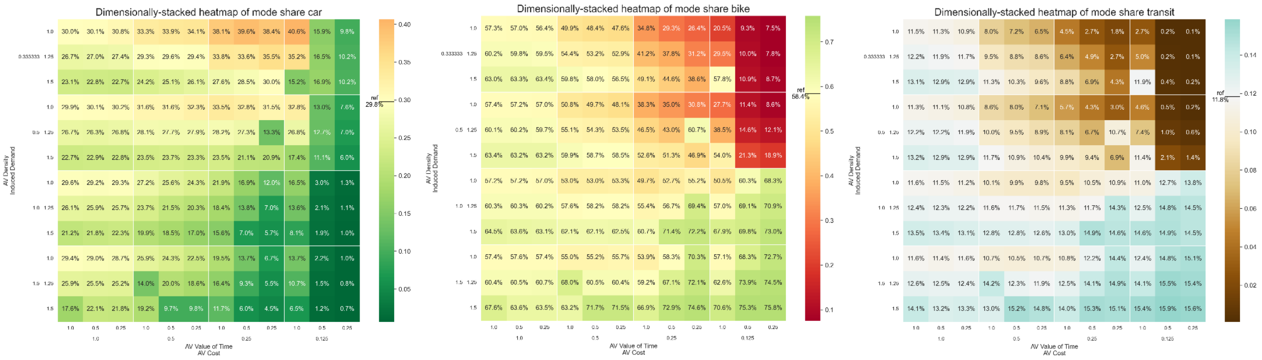


Fig 5.2: Mode share of cars, bicycles, and public transit in different scenarios

Looking at the mode shares of the other modalities, we see again those two distinct futures depending on the density of AVs. If AVs operate inefficiently, bike and transit shares remain high, and car share slightly reduces as AVs get cheaper. However, with high density AVs, bike and transit share drop very steeply while car share remains relatively high. Notably, there even is a spot in which the car share increases, with very high density AVs that are still relatively expensive (a cost factor of 0.5 or 0.25). We will explore this further in 5.2.

It's also remarkable that as AVs get cheaper and more dense, the modal shift from cyclist and transit starts earlier and happens faster than the modal shift from cars.

Finally, the induced demand doesn't seem to matter very much for the mode shares. While in the likely near-future scenarios with expensive AVs the induced demand lowers car and AV share with high induced demand, as AVs get cheaper and adoption increases, the density dictates the mode shares more than the induced demand.

5.2 System effects

With the modal shift and AV adoption patterns established, we now turn to the system-level effects of these changes. This section addresses subquestion C, exploring which undesired urban problems are amplified or reduced by the introduction of self-driving cars.

Road network performance and congestion

Fig 5.3 shows the average car speed, average AV speed, and average network speed in the 144 scenarios. These metrics provide insights into the overall efficiency of the road network and the impact of AV adoption on traffic flow.

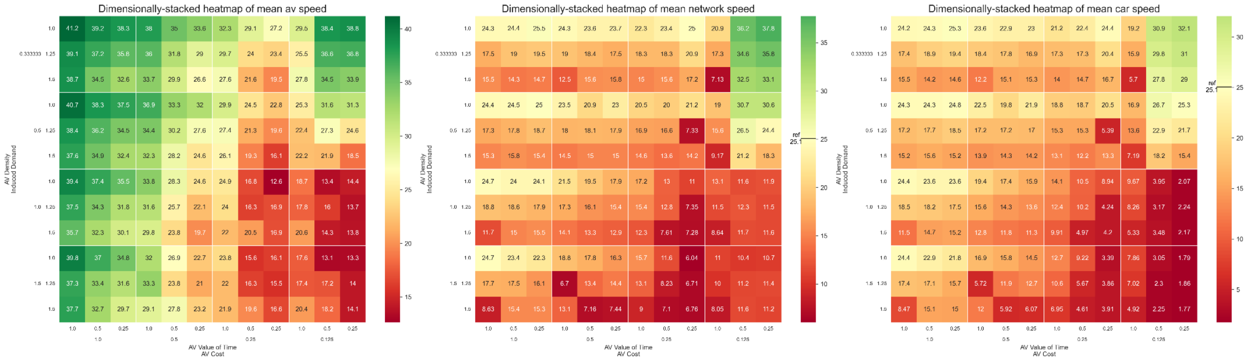


Fig 5.3: Average car speed, average AV speed, and average network speed in different scenarios

In almost all scenarios, the average car speed is reduced compared to the reference scenario without AVs. While about 25 km/h in the reference scenario, it drops to about 18 km/h with 25% more overall demand and below 15 km/h with 50% more demand, suggesting significant congestion. AVs get cheaper, mean car speeds slow down further, in some cases below 5 km/h. With very cheap AVs we see the a similar split as before: with a density of 1.5 and 1.0 the city comes to a griding halt, while a density of 0.5 boosts the speeds back to the reference scenario, suggesting that AVs add about as much road capacity as they take up. Only with a density of 0.333, the speeds are significantly higher than the reference scenario, suggesting that AVs can significantly increase road capacity.

AV speeds show many of the same traits: Higher induced demand lowers speed, cheaper AVs also lower speed, and the same density split, but with one remarkable difference: with a density of 0.333, average AV speeds are significantly higher than the cars. Especially when AVs are expensive, this suggests that people only use AVs when they are relatively fast, and provide significant time savings over bicycles and public transit. As AVs get cheaper, their average speed drops, suggesting both net congestion and that people are taking AVs also for trips with less time savings. Especially with an AV cost of 0.25, the AV VOT factor has very significant impact on the AV speed, suggesting that people with a low VoT are willing to take AVs even if they are slower than other, more expensive modes (including cars).

Finally, the average speeds of all vehicles on the network show the same trend, with it being notable that network speeds will only increase when AVs are both very cheap and very dense. All other scenarios show a significant decrease in network speed, with the most extreme scenarios showing speeds well below 10 km/h.

Figure 5.4 shows the average delay compared to free-flow speeds, and shows very similar patterns. In the reference scenario, vehicle trips take about 70% more time than when they would be able to travel at free-flow speeds. This increases to 120% and almost 200% with 25% and 50% more demand, respectively. Cheaper AVs don’t provide any benefits until they are prices below one eight of the current pricing, and only with a density of at least 0.5. Densities of 1.0 and 1.5 in that case can blow up average delays to over 500%, meaning only one-sixth of the average free-flow speed is achieved.

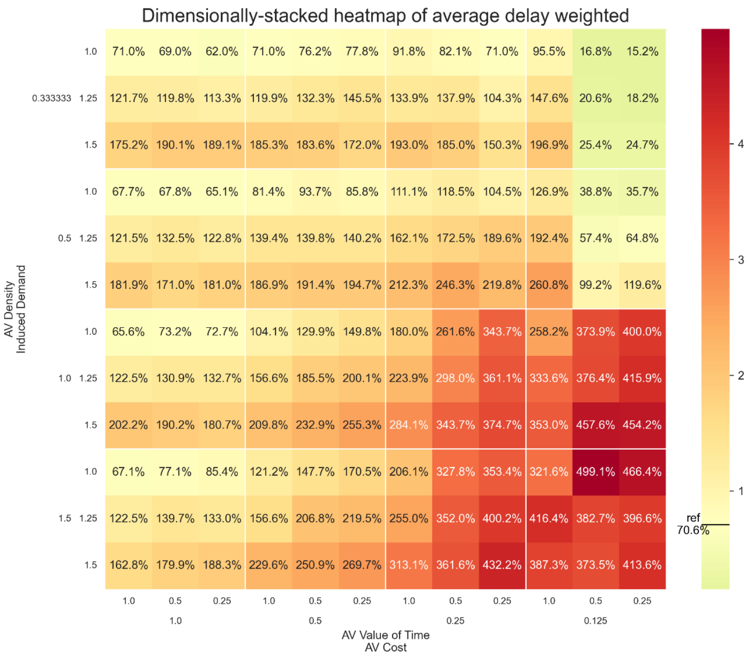


Fig 5.4: Average delay (compared to free flow) in different scenarios

Vehicle distance traveled

Total vehicle distance traveled is useful as a high-level metric because it can act as a proxy for many other metrics, like congestion, emissions, energy use, and wear and tear on the road network. Fig 5.5 shows the total network distance traveled and the average network delay in the 144 scenarios.

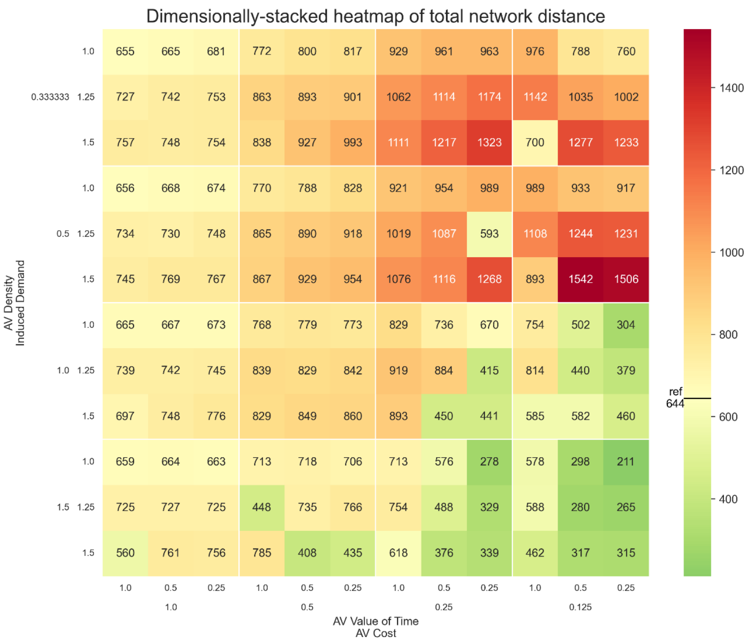


Fig 5.5: Total network distance traveled and average network delay in different scenarios

Interesting, the total network distance traveled only increases slightly with more demand in scenarios with close to current pricing, indicating the network is already close to its maximum capacity. With AVs getting cheaper and adopted, we see the same split as in previous metrics, but in a surprising direction. The total vehicle distance decreased significantly, to under half of the reference scenario, with very cheap AVs and non-dense AVs.

While maybe surprising on the surface level, it is consistent with the conceptual model: Slow moving vehicles don't cover a lot of distance, and a city in gridlock doesn't move a lot of vehicles.

With higher densities, cheap AVs and low value of time, the induced demand starts to matter a lot more, scaling practically linearly with the induced demand factor. This suggests that the speeds on the network are sufficient to accommodate all vehicles that want to travel, leading to large distances covered.

Especially the implication of high speeds with high milage could have severe negative effects in a city. Even if only EVs are considered and not the negative externalities of ICE cars, collisions causing injuries, energy usage, noise pollution, road wear and tear, and microplastics from tire wear could all be significantly increased.

Travel time and perceived costs

Finally, it's interesting to look at the average travel time and the perceived costs of the trips, since those are two of the potential benefits of AVs. These are shown in Fig 5.6.

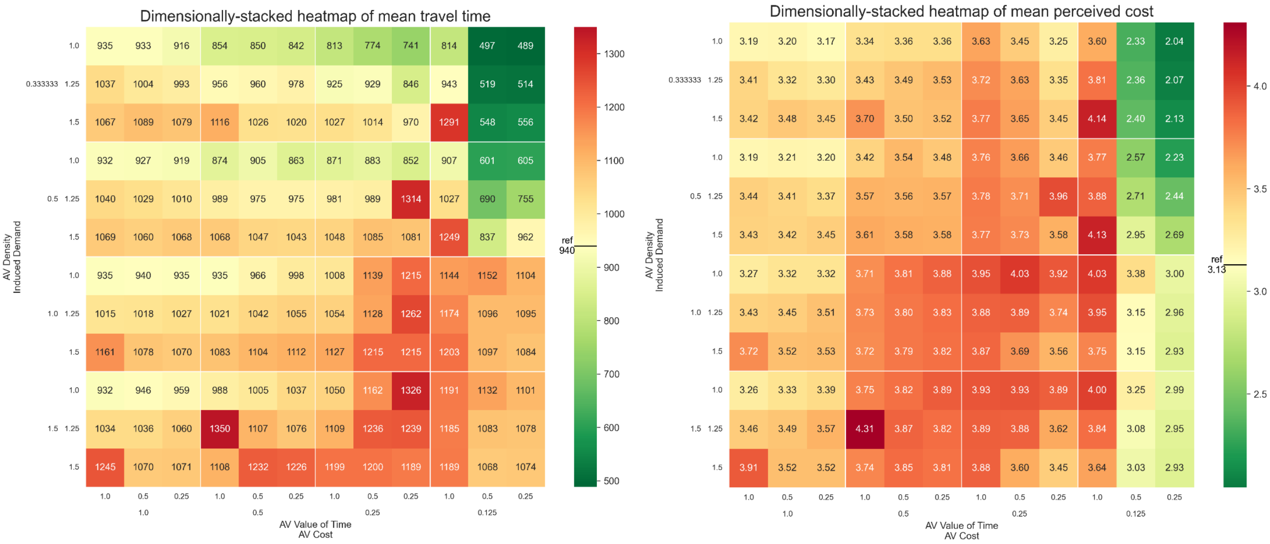


Fig 5.6: Average travel time and average perceived costs in different scenarios

The mean travel time degrades immediately with induced demand. Without any induced demand, we see average travel times increase relatively soon, with an AV costs of 0.5 already leading to notable decreases, as long as the density is 0.5 or 0.333. With a density of 1.0 or 1.5, the opposite happens, and there isn't a single scenario in which AVs with that density improve average travel times. The huge potential of AVs are reached if the density reaches 0.333, almost slashing the average travel time for all travelers in half. A density of 0.5 is also enough as long as induced demand is low.

One very interesting observation is that the AV Value of Time is really important in that last case, and that deserves some further explanation. If the VoT factor for AVs is 0.5 or lower, we see that the AV travel times massively decrease, but not if the VoT factor is 1.0. Understanding this requires looking back at Fig 5.2, which shows a large modal shift from cars to AVs only occurs with those lower VoTs. So if the AV VoT factor is still 1, a significant shift from bikes and public transit to AVs happens, increasing AV share to around 30%, but most people keep driving their cars, and some people even shift from other modalities to cars. This means the total number of regular cars on the road is not reduced and in a few cases even increases, while adding some AVs to the mix. Even if these AVs have optimal density, it still leads to a net increase in car density and thus an increase in congestion and travel times.

The results in the lower right corner indicate that the metrics improve somewhat again as AVs get cheaper and VoT gets lower, but this isn't the case. For both metrics the results there should be disregarded, since not enough travelers were even able to finish their journey to give a representative picture of these two metrics (data for these metrics could only be collected when a journey was finished, and many travelers simply weren't able to before the simulation ended at midnight).

5.3 Policy effectiveness

To address subquestion D about which policies can help mitigate negative impacts of AV adoption while preserving benefits, we evaluated the effectiveness of eight representative scenarios under nine different policy combinations as described in Section 4.2. This section presents the results of the policy analysis, focusing on the impact of speed limit reduction and congestion pricing policies on mode shares, network performance, and total vehicle kilometers traveled.

Similar heatmaps as in the previous sections are shows, but now with the different scenarios on the y-axis and the different policies on the x-axis. Ideally, a policy would lead to better outcomes than the reference policy of doing nothing.

AV adoption and modal shift

Fig 5.7 shows the mode share of cars, AVs, bicycles, and public transit in the 72 scenario-policy combinations. This allows us to see how the policies affect the adoption of AVs and the use of other modes.

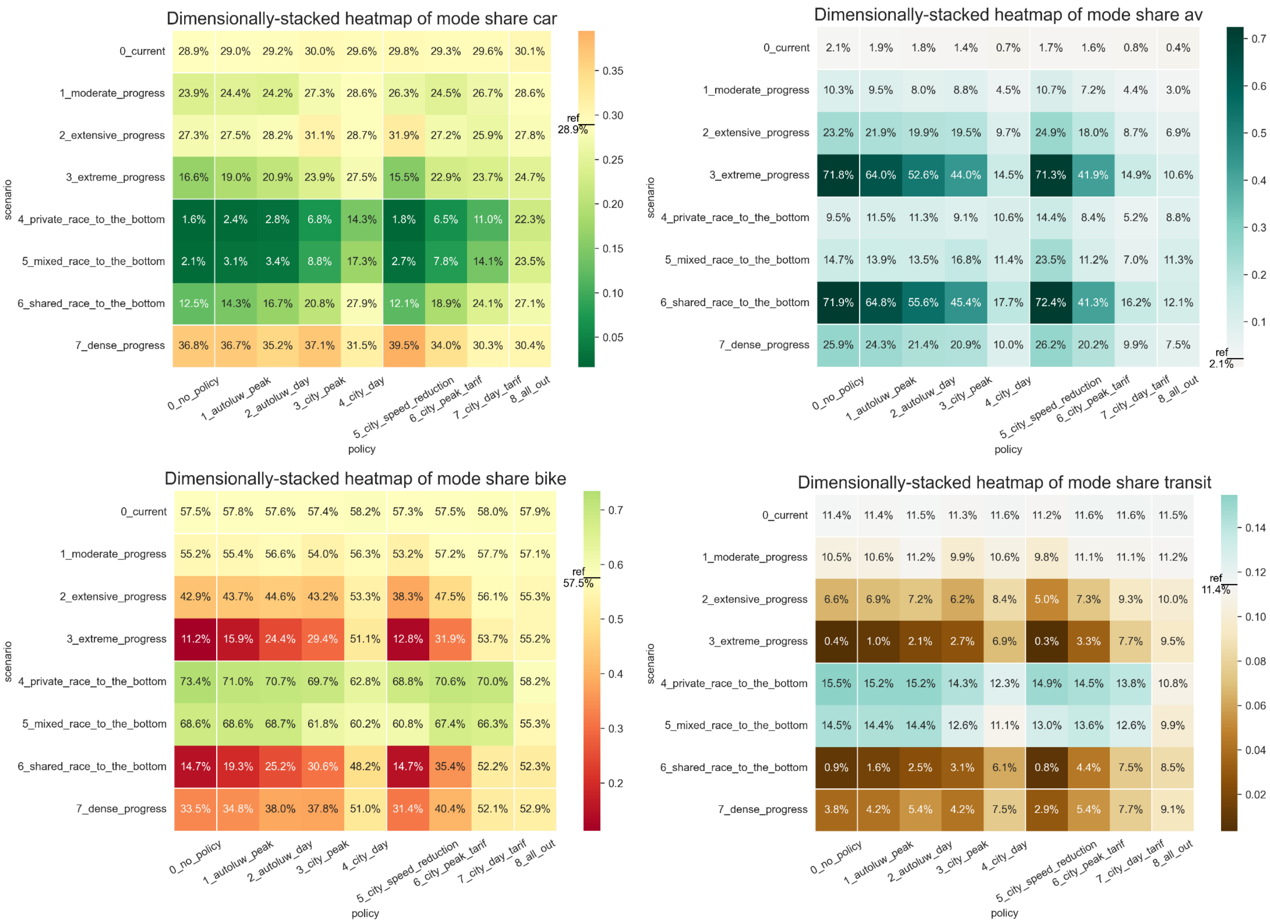


Fig 5.7: Mode share of cars, AVs, bicycles, and public transit in different scenarios and policies

All policies do reduce the AV share, except the speed reduction on its own (even when applied to the whole city, like in policy 5). The comprehensive all out policy, which induces a high €10 tariff on all AV trips within the city and reduces the speed limit by 20 km/h on all roads, reduces AV share the most in all scenarios, bringing it down to about 10% at most. The city-day policy (8), proves the AV share can also be significantly reduced with a lower tariff, and the city-day-tarif policy (7) shows that the speed reduction is not necessary, a city wide tarif dusing the day (6-19h) is reduces AV share on its own.

Looking at the other modalities, the policies mostly dampen the modal shifts from the other modalities to AVs. In some cases, the policies decrease bike and transit use, which is likely caused by reduced congestion and thus more regular car use, but this will be further explored in the next section. None of the policies actually reduce car use, and in some cases even increase it.

System effects

Network performance

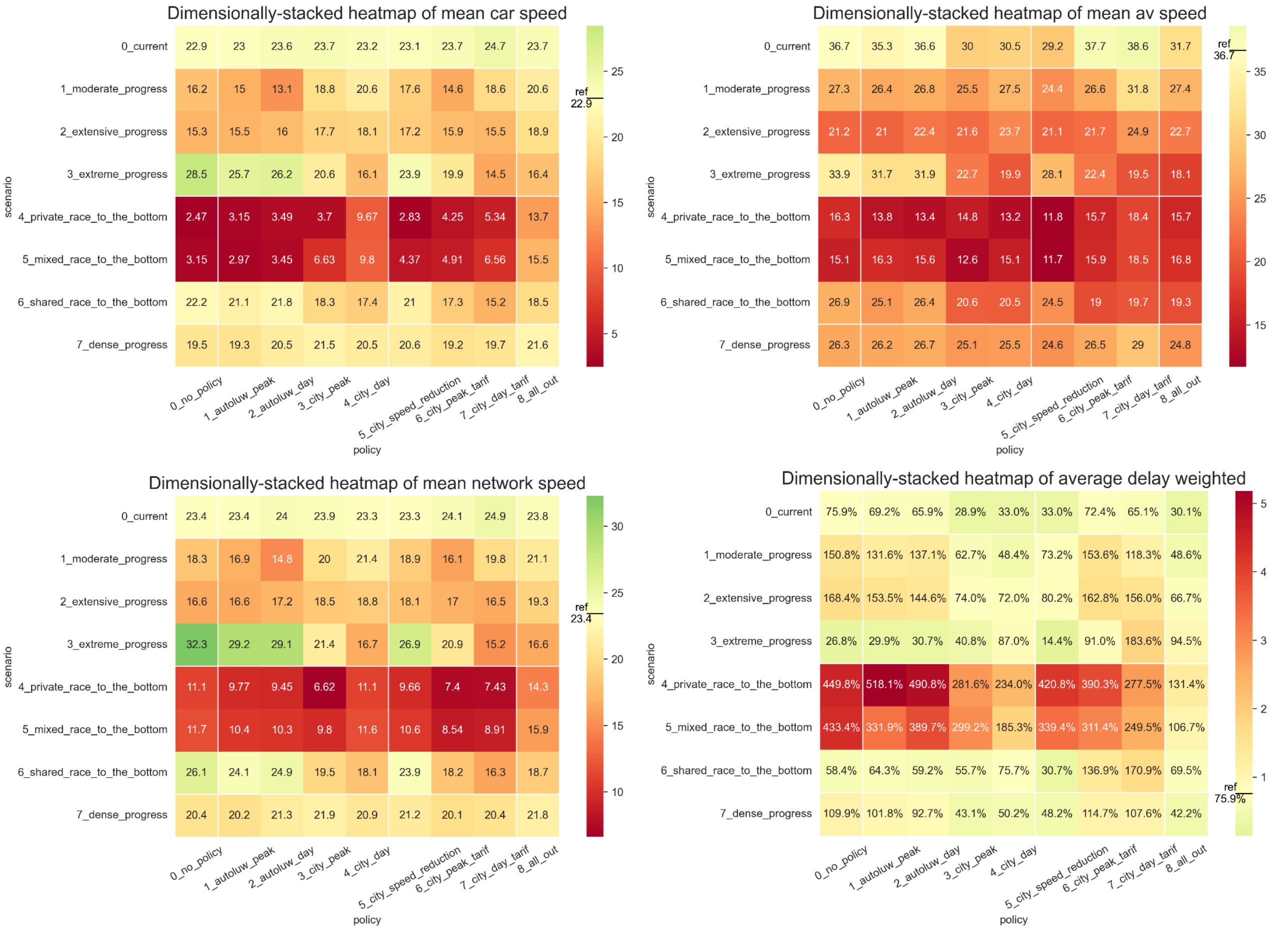


Fig 5.8: Average car speed, average AV speed, average network speed, and average delay in different scenarios and policies

Most policies are surprisingly ineffective in increasing the average car speed, except mainly the all-out (8) and the city-day (4) policies, somewhat. It shows that a city wide tariff combined with a maximum speed reduction can increase car speeds in the moderate-progress and private- and mixed-race-to-the-bottom scenarios (1, 4 and 5). A tariff on its own (7) is less effective, and all other policies don't noticeably help car speeds, showing the small "autoluw" area and tariffs only at rush hours are not very effective.

AV speeds don't share this trend, and get almost universally worse with each policy in each scenario. Only policy 7, with only a tariff, can get AV speeds up in some scenarios, likely because relatively more fast routes are taken, since network speeds don't show significant improvements.

Finally, there is no policy that improves any of the speed metrics in each scenario. Policies that help in heavily congested scenarios, mainly by getting inefficient AVs off the road, do active harm in other scenarios, where high-density AVs get replaced with cars that are less efficient. No strategy is dominant on any metric, let alone on all. There is no silver bullet.

Note that the delay metric is lower with the speed limit reduction, but the average network speed is also lower. This is due to the way delay is measured: it's a ratio of the actual travel time divided by the free-flow travel time. If the free-flow travel time is higher (due to the speed limit reduction), the delay will be lower, even if the actual travel time is higher. It might influence the perception of congestion, since the difference between the actual travel time and the free-flow travel time is smaller, but it doesn't actually reduce congestion.

Vehicle distance traveled

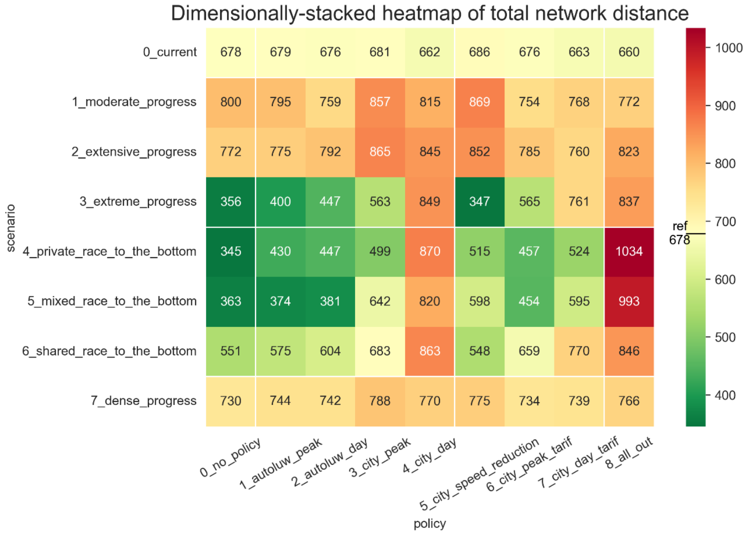
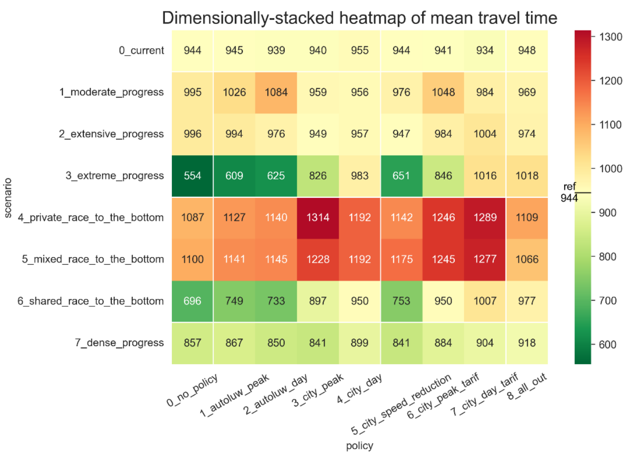


Fig 5.9: Total network distance traveled and average network delay in different scenarios and policies

Vehicle distance traveled is a very mixed bag. A few more drastic policies, like the city-day (4) and all-out (8) increase the distance traveled on practically in all cases. These were the policies that were effective in increasing network speeds, which shows here.

No policies effectively reduce vehicle distance. It shows that more comprehensive policies are needed that also target other modalities than AVs, which also might need to be more fine-grained, dynamic and/or adaptable if reducing vehicle milage is a goal.

Travel time and perceived costs



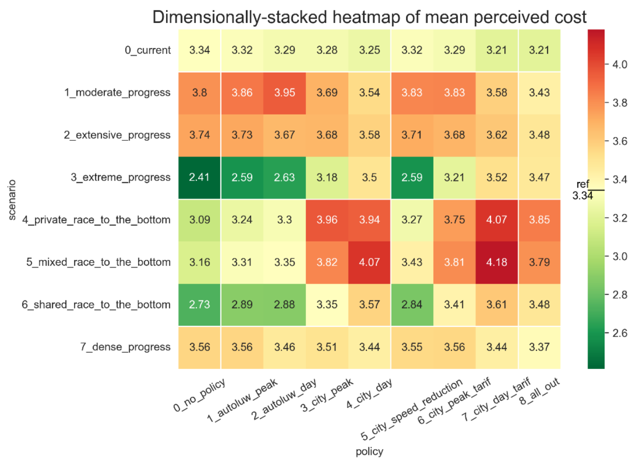


Fig 5.10: Average travel time and average perceived costs in different scenarios and policies

There is no single policy that manages to reduce travel time significantly. It shows just slapping a price and speed reduction on AVs at some time in some area doesn't help in that regard. Only in the moderate and extensive progress scenarios (1 and 2) some of the more aggressive policies seem to reduce travel times slightly, with notably the city-peak pricing policy (3) having a positive effect for the first time.

Perceived costs show a largely the same patterns, but in this case the more comprehensive policies (4 and 7, 8) are able to reduce the perceived costs somewhat in scenarios 1, 2 and 7. In all other scenarios and all other policies generally increase the perceived costs, showing again that there is no silver bullet.

5.4 Overview

The results from the scenario and policy analysis delivers some distinct insights in how autonomous vehicles might be adopted, what the potential undesired effects are, and which policies might help mitigate those effects. The main findings are:

First, AV adoption appears to be primarily driven by cost, with significant adoption only occurring when costs drop below half of current levels. The value of time spent in AVs plays a secondary but important role, particularly in determining whether people switch from cars to AVs. When AVs are very cheap (one-eighth of current costs) and time is perceived as more valuable in them (VOT factor of 0.5 or lower), adoption can reach over 65% of trips. However, this high adoption scenario only materializes if AVs can operate efficiently (density factor of 0.5 or lower).

Second, the density of AVs emerges as a critical factor that creates two distinct futures. With inefficient AVs (density factors of 1.0 or 1.5), increased adoption leads to severe congestion, with average network speeds dropping below 10 km/h in extreme cases. Conversely, with efficient AVs (density factors of 0.333 or 0.5), the system can accommodate high adoption while maintaining or even improving traffic flow. This bifurcation suggests that the success of AVs in urban environments may depend more on their space efficiency than their cost or comfort advantages.

Third, the modal shift patterns reveal that cyclists and transit users are more likely to switch to AVs than car users when AVs become cheaper. This suggests that AVs might compete more directly with sustainable transport modes than with private cars, potentially undermining urban sustainability goals. The effect is particularly pronounced when AVs are both cheap and space-efficient, leading to significant reductions in bicycle and transit mode shares.

Fourth, induced demand plays a complex role. Its effects are most noticeable in scenarios with efficient AVs, where the additional capacity enables the system to accommodate more trips. In scenarios with inefficient AVs, the system is already so congested that induced demand has limited additional impact. This suggests that the relationship between AV adoption and induced demand is non-linear and heavily dependent on AV operating characteristics.

Fifth, vehicle distance traveled reveals complex patterns depending on AV efficiency and speed. In scenarios with inefficient AVs (density 1.0-1.5), total vehicle kilometers decrease significantly as congestion reduces speeds, sometimes to less than half the reference scenario. Conversely, with efficient AVs (density 0.333-0.5), vehicle kilometers can increase substantially, scaling almost linearly with induced demand. This divergence is particularly pronounced when AVs are very cheap (cost factor 0.125) and perceived time costs are low (VOT factor 0.25-0.5), suggesting that efficiency improvements could lead to significantly more vehicle travel.

Sixth, policy analysis reveals that most of the policies evaluated are ineffective or even counterproductive across different scenarios. Speed reductions alone (policy 5) show practically no benefit on any metric, failing to improve network performance or encourage sustainable mode choices. The “autoluw” area policies (1 and 2) prove too limited in scope to affect system-wide metrics meaningfully. Even city-wide peak-hour congestion pricing (policy 6) shows minimal positive impact, only marginally reducing AV adoption without improving overall system performance.

More comprehensive policies, like the city-day (4) and all-out (8) interventions, show some ability to influence system behavior but often with significant trade-offs. While they can increase car speeds in scenarios with inefficient AVs (density 1.0-1.5), they simultaneously reduce AV speeds and increase total vehicle distance traveled. In scenarios with efficient AVs (density 0.333-0.5), these same policies can actually harm system performance by discouraging the use of more efficient vehicles. The city-wide tariff policy (7) demonstrates that speed reductions are often unnecessary - pricing alone can achieve similar effects with less disruption to network performance.

Perhaps most tellingly, no policy consistently improves all metrics across different scenarios. Policies that help in heavily congested scenarios with inefficient AVs actively harm performance in scenarios with efficient AVs. Even when policies successfully reduce AV adoption, they often fail to improve - and sometimes worsen - key metrics like average travel time, perceived costs, and network efficiency. This suggests that simple, static policies targeting AVs alone may be insufficient for managing the complex dynamics of future urban transportation systems.

6. Discussion

After having shown the model results, in the discussion we contextualize these findings within existing research, examines their implications, and identifies areas for future investigation.

6.1 Key findings in context

First, the five key findings presented in 5.4 will be reflected upon and placed in scientific context.

Cost-driven adoption with critical thresholds

Our finding that significant AV adoption only occurs when costs drop below 50% of current levels aligns with previous research by Talebian & Mishra (2018), who found that aggressive price reductions (15-20% annually) were necessary for widespread adoption. However, our results reveal a more nuanced relationship between cost and adoption than previously identified. While Talebian & Mishra found a relatively straightforward relationship between price reductions and adoption rates, our results show distinct tipping points where adoption accelerates rapidly, particularly when costs fall below 25% of current levels. While four variable levels is by far not enough to estimate a clear adoption pattern, it might imply an S-curve pattern, which does occur more often in technology adoption (Rogers, 1962).

This non-linear adoption pattern emerges from the interaction between cost reductions and other system factors, particularly AV density. The simulation deliberately separated these factors to understand their individual impacts - in reality, cost reductions might come from the same technological advances that improve operational efficiency. This separation revealed that even dramatic cost reductions alone are insufficient to drive high adoption in urban environments if AVs operate inefficiently.

The critical role of AV density

Perhaps our most significant finding is the identification of AV density as the critical factor determining system outcomes. This aligns with but substantially extends previous research. While Fagnant and Kockelman (2015) estimated that cooperative adaptive cruise control could increase lane capacities by 1-80% depending on market penetration, their analysis focused primarily on the positive potential of efficient operations. Our results demonstrate that inefficient AVs can actually reduce system capacity, creating a stark bifurcation in possible futures.

Importantly, our model treated density as an outcome-based metric rather than specifying how it's achieved. A density factor of 0.5 could result from various combinations of: - Smaller vehicle sizes - More efficient vehicle spacing through faster reaction times - Better routing and scheduling to reduce empty trips - Network-level optimizations - Higher average occupancy through ride-sharing

This approach allows the results to remain relevant regardless of which technological or operational solutions ultimately emerge. The critical threshold identified (density factors below 0.5) provides a clear target for AV developers and policymakers, while remaining agnostic about how this target is achieved.

Modal shift patterns

Our observation that cyclists and transit users are more likely than car users to switch to AVs challenges common assumptions about AV adoption patterns. While this aligns with research on current ride-hailing services (Graehler et al., 2019), the magnitude of the shift in our simulations is notably larger. This difference likely stems from two factors: 1. The model's important role of travel time value, which captures how AVs might make longer trips more acceptable by enabling productive use of travel time. 2. The explicit modeling of trip chains, which reveals how car ownership creates "lock-in" effects that resist modal shifts

This finding has particularly important implications for cities like Rotterdam with high cycling mode shares. Previous research has often focused on car-to-AV transitions, potentially underestimating the risk to sustainable transport modes.

System-level effects

The emergence of distinct futures based on AV density adds important nuance to debates about induced demand. Our results align with Metz's (2018) observation that AVs' impact will largely depend on whether they operate as private or shared vehicles. However, our findings suggest that the critical factor isn't ownership models per se, but rather the resulting space efficiency of operations.

The interaction between induced demand and AV efficiency revealed in our results extends Lee et al.'s (1999) work on equilibrium responses to transportation improvements. While their research suggested 10-20 years for full equilibrium adaptation, our results indicate that the speed and nature of this adaptation may vary dramatically depending on AV operating characteristics. In scenarios with efficient AVs, the system can accommodate significantly more induced demand, while inefficient AV scenarios show rapid degradation of service levels even without additional demand.

The relationship between AV density and vehicle kilometers traveled (VKT) revealed in our results adds important nuance to previous research on transportation system impacts. VKT can serve as a proxy for multiple urban externalities including particulate emissions, noise, infrastructure wear, and safety risks - effects that persist even with zero-emission vehicles. Importantly, the source of improved AV density significantly influences these impacts. If density improvements come from increased vehicle occupancy, total VKT could decrease as trips are combined. However, if improvements stem from technical efficiency gains like smaller vehicles or reduced following distances, VKT will likely remain high or increase as the freed capacity enables more trips.

Policy effectiveness

The limited effectiveness of traditional policy interventions across different scenarios represents a novel finding with important implications. While previous research has focused on optimal policy design for specific AV scenarios, our results suggest that policies optimized for one scenario may be counterproductive in others. This creates a fundamental challenge for policymakers: how to design interventions that remain effective across multiple possible futures.

The finding that smaller-scale interventions (like the "autoluw" area policies) had minimal impact aligns with network theory predictions about the limitations of localized traffic interventions in connected systems. However, the observation that even city-wide interventions showed limited effectiveness in many scenarios suggests deeper challenges in managing AV adoption through traditional policy tools. It should be noted that the focus of this research was to explore the adoption patterns and uncertainty space, and was chosen to limit the policy analysis in scope. There might be other policies that are effective on more metrics among more scenarios.

6.2 Policy implications

The complex dynamics revealed by this research pose significant challenges for policymakers, requiring a fundamental rethinking of traditional transportation policy approaches. The results suggest several key areas where policy intervention is critical, but also reveal why conventional approaches may be insufficient.

The primacy of space efficiency in determining system outcomes suggests that this should be the central focus of AV regulation. While previous policy discussions have emphasized safety, liability, and data privacy (Fagnant & Kockelman, 2015), our results indicate that space efficiency requirements may be equally important for urban environments. Cities should establish clear performance metrics for AV operations that focus on their space consumption per passenger, rather than treating all AVs as equivalent. This might involve differentiated road pricing based on vehicle occupancy, dedicated infrastructure access for high-efficiency services, or operational requirements for minimum passenger densities in certain areas.

However, the implementation of such policies faces several challenges. First, space efficiency is an emergent property of multiple factors, including vehicle size, operational patterns, and passenger occupancy. Policy frameworks need to focus on outcomes rather than prescribing specific technological solutions, allowing innovation while ensuring system-level benefits. Second, the measurement and enforcement of such requirements requires new monitoring capabilities and regulatory frameworks. Third, policies need to account for the transition period where conventional and autonomous vehicles share the road network.

The vulnerability of sustainable transport modes to AV competition represents another crucial policy challenge. Traditional approaches to protecting public transit and cycling have focused on infrastructure provision and operational priority. While these remain important, our results suggest they may be insufficient in the face of cheap, comfortable AVs. Cities need more comprehensive approaches that integrate AVs into a sustainable mobility ecosystem rather than treating them as competitors to be restricted. This might involve designing AV services specifically to complement rather than replace existing sustainable modes, using them to solve first/last mile challenges or serve areas with poor transit coverage.

The stark differences between scenarios with different AV characteristics necessitate adaptive policy frameworks. Static regulations designed for current conditions may become either too restrictive or too permissive as AV technology evolves. Instead, cities need dynamic policy frameworks that can adjust automatically based on observed system performance. This represents a significant departure from traditional transportation policy, which typically changes slowly and reactively. The development of such adaptive frameworks requires not just new policy tools, but also new institutional capabilities for monitoring and responding to changing conditions.

The potential for increased vehicle kilometers traveled in high-efficiency AV scenarios suggests that cities need policies addressing absolute mobility levels, not just focusing on traditional metrics like congestion and travel times. For instance, road pricing could differentiate between single-occupancy and shared AVs, rewarding higher vehicle occupancy rather than just operational efficiency. Infrastructure access policies could prioritize AVs that demonstrably reduce total vehicle kilometers through trip chaining or ride-sharing, rather than treating all AVs equally. VKT should also probably be normalized by some factors, like weight. Such policies would need to carefully balance the mobility benefits of efficient AVs against their potential to induce additional vehicle travel and associated externalities like tire wear, noise, and infrastructure degradation - impacts that persist even with zero-emission vehicles.

The limited effectiveness of localized interventions revealed in our simulations suggests the need for coordinated policy approaches across different spatial scales. While cities may be tempted to implement restrictions in specific problematic areas, our results indicate that such approaches may simply shift problems elsewhere in the network. System-level policies that address both supply and demand aspects of AV operations are likely to be more effective. This might involve coordinated pricing schemes across entire urban regions, integrated planning of AV services with public transit networks, and consistent regulations across jurisdictional boundaries.

Perhaps most importantly, cities need to plan carefully for the transition period. The potential for rapid shifts in travel patterns once certain thresholds are crossed (in cost, comfort, or efficiency) means that cities cannot wait to observe problems before responding. Proactive planning should include clear triggers for policy interventions based on monitored metrics, strategies for protecting vulnerable users during the transition, and mechanisms for adjusting existing infrastructure and services as travel patterns change.

6.3 Future research

This study's findings, while showing several dynamics of AV adoption in urban environments, also highlight important areas for future research. Both the methodological approach and the results suggest promising directions for deeper investigation, which can be divided into two categories: improvements to the current modeling approach and broader research needs in the field of urban transportation transitions.

Model and study improvements

The most pressing opportunity for methodological improvement lies in the agent behavior model. While the current rational choice framework provided useful insights, it likely oversimplifies the complexity of travel decisions, particularly regarding new technologies like autonomous vehicles. An activity-based travel demand model would better capture the interdependencies between trips and daily activity patterns. This isn't merely a matter of adding complexity - understanding how AVs might reshape daily activity patterns is crucial for predicting their systemic impacts. For example, the ability to work while traveling could fundamentally alter the relationship between home and workplace location choices, a dynamic the current model cannot capture.

Implementing such an activity-based approach would require carefully designed stated preference studies. Current revealed preference data, while valuable for validating existing travel patterns, cannot capture how people might respond to technologies that don't yet exist in their full form. These studies should investigate not just mode choice in isolation, but how different AV service configurations might influence activity scheduling, destination choices, and the perceived value of travel time. The heterogeneity in these responses - how different demographic groups might value and use AVs differently - could significantly affect adoption patterns and system-level outcomes.

The traffic simulation component, while adequate for examining system-level effects, could benefit from more detailed representation of intersection dynamics. The current approach using default merge priorities may underestimate the potential for local congestion points, particularly in dense urban areas where intersection capacity often constrains network performance. More sophisticated modeling of traffic signals, turn movements, and yielding behavior could reveal additional challenges or opportunities in managing mixed autonomous and conventional vehicle traffic. However, this increased detail would need to be balanced against computational constraints - the ability to run large numbers of scenarios was crucial for understanding system behavior under uncertainty. Data availability might also be a challenge here.

The most significant data limitation was the lack of time-varying travel times for non-car modes. While bicycle and transit travel times are generally more stable than car travel times, they do vary throughout the day, particularly for transit where service frequencies change. Collecting this data was prohibitively expensive with current API pricing models, but future research could benefit from partnerships with transit agencies and mobility data providers to obtain more comprehensive temporal coverage. This would be particularly valuable for understanding how AV services might compete with or complement public transit during different times of day.

Broader research directions

Beyond improving the current model, this study points to several crucial areas requiring broader investigation. Perhaps most fundamental is the need to understand the long-term dynamics of AV adoption and its impacts on urban form. While our model focused on transportation system effects, the potential for AVs to reshape land use patterns could be equally significant. The relationship between transportation and land use has historically been bidirectional - new transportation technologies enable new development patterns, which in turn influence travel demand. Understanding these feedback loops in the context of AVs requires integrating transportation models with land use and economic models over longer time horizons. Either find a few orders of magnitude in computational efficiency, or prepare your supercomputer.

The limitations of static policies revealed in our results suggest an urgent need for research into adaptive policy frameworks. Traditional transportation policies often change slowly and reactively, but our findings indicate that AV adoption could create rapid shifts in travel patterns once certain thresholds are crossed. Future research should explore how cities can develop policies that automatically adjust based on observed conditions - for example, dynamic pricing schemes that respond to both congestion levels and AV adoption rates. This requires not just technical solutions but also investigation of the legal and institutional frameworks needed to implement such adaptive approaches.

The stark differences we observed between scenarios with different AV operating characteristics highlights the need for research into the determinants of AV space efficiency. While our model treated density as an outcome-based metric, understanding how to achieve higher density through vehicle design, operational strategies, and policy incentives is crucial. This might involve detailed studies of AV behavior in mixed traffic, optimization of fleet operations, and analysis of the trade-offs between individual vehicle performance and system-level efficiency.

Social equity implications of AV adoption deserve particular attention in future research. Our results suggesting that cyclists and transit users might be more likely to switch to AVs than car users raises important questions about the distribution of benefits and burdens. If AVs primarily attract users away from sustainable modes rather than private cars, this could exacerbate rather than alleviate urban transportation problems. Research is needed on how policies can ensure that AV services complement rather than compete with sustainable transport modes, and how the benefits of automation can be equitably distributed across different demographic groups.

Finally, the interaction between AVs and other emerging technologies requires deeper investigation. Our model treated AVs as an isolated technological change, but in reality, they will develop alongside other innovations in energy systems, communications infrastructure, and shared mobility services. Understanding these interactions is crucial for both public policy and private investment decisions. For example, the potential for AVs to serve as mobile energy storage units could significantly influence both transportation and energy system planning, while integration with mobility-as-a-service platforms could affect adoption patterns and service models.

These research directions suggest that while this study has provided valuable insights into potential AV impacts and policy responses, many important questions remain. Future work will need to combine detailed technical analysis with broader systemic thinking to help cities navigate the transition to automated mobility. It's important to recognize the heterogeneity of different urban environment and their existing policies: not cities are alike. The complexity of urban transportation systems and the potentially transformative nature of AVs demand research approaches that can capture both immediate operational impacts and longer-term structural changes.

7. Conclusions

This research demonstrates that autonomous vehicles' impact on urban mobility problems appears to depend more strongly on their space efficiency than on cost or comfort advantages. While previous research has focused on adoption rates and individual benefits, our findings suggest that the system-level effects of AVs may create distinct trajectories in possible urban futures, primarily influenced by their density factor - the space required per person transported relative to conventional vehicles. The model indicates a potentially critical threshold around a density factor of 0.5, below which AVs can maintain system performance even at high adoption rates. Above this threshold, increased AV adoption tends to degrade network performance regardless of other characteristics.

However, even scenarios with highly efficient AVs present significant challenges: they tend to induce substantially more vehicle kilometers traveled, which could increase energy consumption, road wear, tire particle emissions, and noise pollution even with zero-emission vehicles. Our research only looked at short-term modal shifts, the increased mobility and reduced perceived cost of travel time might also encourage urban sprawl, potentially undermining other sustainability goals. This suggests that every potential AV future brings its own set of challenges that require careful consideration and management.

Another notable - and somewhat concerning - finding is that AVs appear to compete more directly with sustainable transport modes than with private cars. This competition intensifies as AVs become cheaper and more comfortable, potentially affecting cycling and public transit usage. The model suggests this shift might begin even before significant car-to-AV transitions. If accurate, this could create a transition period in which AVs exacerbate rather than alleviate urban transportation problems.

The limited effectiveness of traditional policy interventions across different scenarios suggests that cities may need to consider new approaches to transportation policy. Static, spatially-limited interventions showed particular limitations in the model, while even comprehensive city-wide policies demonstrated constraints in simultaneously preserving benefits and mitigating negative impacts. This indicates that managing AV adoption might require more finegrained steering mechanisms and/or more dynamic policy frameworks, though further research would be needed to determine optimal approaches.

Several crucial aspects of AV integration remain poorly understood and warrant further investigation. The interaction between AV operations and parking behavior could significantly affect urban space use and travel patterns, particularly during the transition period with mixed autonomous and conventional vehicles. The logistics of charging infrastructure may constrain operational efficiency and influence service patterns. Personal preferences, habits, and psychological factors in adoption decisions likely play a more complex role than our rational choice model captures. Perhaps most importantly, the long-term effects on land use patterns and urban development remain uncertain, as improved mobility could reshape where people choose to live and work.

This research suggests that autonomous vehicles may represent neither an inherent solution nor an inevitable problem for urban mobility. Rather, their impact appears likely to depend on the interaction between their operating characteristics, adoption patterns, and policy frameworks. Further research will be crucial to validate these findings and explore additional factors that could influence AV integration into urban transportation systems.

The significant variations between potential futures revealed by this research - ranging from improved mobility to system strain - emphasize the potential importance of early policy consideration in AV development. The network effects and behavioral patterns identified in our model suggest that early trajectory decisions could have lasting implications. Governments, regulators and industry stakeholders should start working on truly understanding this vastly complex system, and on how to steer to a future in which AVs support urban sustainability, connectivity, and livability, rather than letting market forces spin the wheel of fortune.

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Appendices

Appendix A: Model description

The model description follows the ODD (Overview, Design concepts, Details) protocol (Grimm et al., 2006, 2020). This protocol provides a standardized format for describing agent-based models, ensuring clarity and reproducibility.

1. Purpose

The purpose of this model is to simulate the introduction and adoption of self-driving cars (autonomous vehicles, AVs) in urban environments, specifically focusing on the Rotterdam area in the Netherlands. The model aims to explore the system-level effects of AVs on urban transportation, including changes in mode choice, traffic patterns, and potential unintended consequences. By simulating individual agent behaviors and their collective outcomes, the model seeks to answer the following key questions:

1. How does the introduction of self-driving cars affect mode choice and travel patterns in urban areas?
2. What are the potential undesired effects of self-driving cars on urban transportation systems?
3. How do different policies influence the adoption and impact of self-driving cars?

The model is designed to provide insights for urban planners, policymakers, and transportation engineers to support decision-making in preparation for the widespread adoption of autonomous vehicles.

2. Entities, State Variables, and Scales

2.1 Entities

The model consists of the following main entities:

1. **Travelers (Agents)**: Represent individual residents of the urban area who make travel decisions.
2. **Urban Model**: Represents the overall simulation environment, including the transportation network and global variables.
3. **UXsim World**: Represents the traffic simulation environment, including road network and vehicle movements.
4. **Journeys**: Represent individual trips made by travelers.

2.2 State Variables

2.2.1 Traveler (Agent) State Variables

- *unique_id*: Unique identifier for each agent
- *pc4*: 4-digit postal code of the agent's location
- *mrdh65*: MRDH (Metropoolregio Rotterdam Den Haag) region number
- *mrdh65_name*: Name of the MRDH region
- *has_car*: Boolean indicating whether the agent owns a car
- *has_license*: Boolean indicating whether the agent has a driver's license
- *has_bike*: Boolean indicating whether the agent has a bicycle (default is True)
- *available_modes*: List of available transportation modes

- *currently_available_modes*: List of currently available transportation modes
- *vot_factor*: Value of time factor (lognormally distributed)
- *value_of_time*: Dictionary of value of time for different modes
- *current_location*: Current location (postal code) of the agent
- *current_vehicle*: Current vehicle being used by the agent
- *traveling*: Boolean indicating whether the agent is currently traveling
- *reschedules*: Number of times the agent has rescheduled trips
- *journeys_finished*: Number of completed journeys
- *costs*: Total costs incurred by the agent
- *time_costs*: Total time costs incurred by the agent
- *trip_times*: List of scheduled trip times
- *destinations*: List of trip destinations
- *journeys*: List of Journey objects representing completed and ongoing trips

2.2.2 Urban Model State Variables

- *step_time*: Time step of the simulation (in hours)
- *start_time*: Start time of the simulation (in hours)
- *end_time*: End time of the simulation (in hours)
- *choice_model*: Type of mode choice model used
- *enable_av*: Boolean indicating if AVs are enabled in the simulation
- *av_cost_factor*: Cost factor for AVs
- *av_vot_factor*: Value of time factor for AVs
- *ext_vehicle_load*: External vehicle load factor
- *uxsim_platoon_size*: Platoon size for UXsim traffic simulation
- *car_comfort*: Comfort factor for cars
- *bike_comfort*: Comfort factor for bicycles
- *av_density*: Density factor for AVs
- *induced_demand*: Factor for induced demand
- *policy_tarif*: Tariff for policy implementation
- *policy_tarif_time*: Time period for policy tariff
- *policy_speed_reduction*: Speed reduction factor for policy
- *policy_area*: Area where policy is applied
- *available_modes*: List of available transportation modes
- *transit_price_per_km*: Price per kilometer for public transit
- *car_price_per_km_variable*: Variable cost per kilometer for cars
- *car_price_per_km_total*: Total cost per kilometer for cars
- *av_initial_costs*: Initial costs for using an autonomous vehicle
- *av_costs_per_km*: Cost per kilometer for autonomous vehicles
- *av_costs_per_sec*: Cost per second for autonomous vehicles
- *default_value_of_times*: Default values of time for different modes
- *comfort_factors*: Comfort factors for different modes
- *pop_dict_pc4_city*: Dictionary of population by postal code
- *mrdh65s*: List of unique MRDH regions in the simulation
- *pc4s*: List of unique postal codes in the simulation
- *trips_by_hour_chance*: Dictionary of trip probabilities by hour

- *trips_by_mode*: Dictionary tracking the number of trips by mode
- *trips_by_hour_by_mode*: Nested dictionary tracking trips by hour and mode
- *uxsim_data*: Dictionary storing UXsim simulation data
- *parked_per_area*: Dictionary tracking parked vehicles by area
- *parked_dict*: Dictionary tracking parked vehicles over time
- *successful_car_trips*: Counter for successful car trips
- *failed_car_trips*: Counter for failed car trips

2.2.3 UXsim World State Variables

- *name*: Name of the simulation
- *deltan*: Platoon size (number of vehicles per platoon)
- *reaction_time*: Reaction time of vehicles
- *duo_update_time*: Time interval for dynamic user equilibrium updates
- *duo_update_weight*: Weight for dynamic user equilibrium updates
- *duo_noise*: Noise factor for route choice
- *eular_dt*: Time step for Eulerian traffic state computation
- *eular_dx*: Spatial step for Eulerian traffic state computation
- *random_seed*: Seed for random number generation
- *tmax*: Total simulation duration
- *node_pc4_dict*: Dictionary mapping postal codes to network nodes
- *node_mrdh65_dict*: Dictionary mapping MRDH regions to network nodes

2.2.4 Journey State Variables

- *agent*: Reference to the agent making the journey
- *origin*: Origin of the journey (postal code)
- *destination*: Destination of the journey (postal code)
- *mode*: Chosen mode of transport
- *start_time*: Start time of the journey
- *travel_time*: Estimated travel time
- *end_time*: End time of the journey
- *distance*: Journey distance
- *cost*: Monetary cost of the journey
- *perceived_cost*: Perceived cost (including time value)
- *comf_perceived_cost*: Comfort-adjusted perceived cost
- *used_network*: Boolean indicating if the journey used the road network
- *available_modes*: List of available modes for this journey
- *perceived_cost_dict*: Dictionary of perceived costs for all available modes
- *started*: Boolean indicating if the journey has started
- *finished*: Boolean indicating if the journey has finished
- *act_travel_time*: Actual travel time (for car/AV journeys)
- *act_perceived_cost*: Actual perceived cost (for car/AV journeys)
- *o_node*: Origin node in the road network
- *d_node*: Destination node in the road network
- *vehicle*: Vehicle object for car/AV journeys

2.3 Scales

- **Spatial scale**: The model covers the Rotterdam urban area, represented by 125 4-digit postal code (PC4) regions within 21 MRDH (Metropoolregio Rotterdam Den Haag) areas.
- **Temporal scale**: The simulation typically runs from 5:00 to 24:00 (19 hours) with a default step time of 5 minutes (1/12 hour).
- **Population scale**: The model simulates approximately 100,000 agents, with each agent representing a platoon of vehicles (default size 10), approximating the actual population of 991,575 in the area.

3. Process Overview and Scheduling

The model follows a discrete event simulation approach, with the following main processes:

1. **Initialization**:
    - Set up the simulation environment and parameters
    - Create agents and assign them to locations based on population data
    - Initialize the road network and traffic simulation (UXsim)
    - Assign car ownership and driver's licenses based on postal code data
2. **Generate trip times and destinations**:
    - Each agent generates a set of trip times based on hourly probabilities
    - Destinations are assigned for each trip based on origin-destination matrices
3. **Start journey**:
    - Determine available modes for the journey
    - Choose origin and destination nodes (for car and AV trips)
    - Select travel mode using the specified choice model
    - Schedule the trip in the traffic simulation (for car and AV trips)
4. **Execute simulation step**:
    - Update the traffic simulation (UXsim)
    - Collect data on traffic conditions and parking
5. **Finish journey**:
    - Update agent's location and available modes
    - Schedule the next journey if available
6. **Add external vehicle load**:
    - Add vehicles representing external traffic at specified intervals
7. **Data collection and analysis**:
    - Collect data on mode choices, travel times, and system-level metrics
    - Analyze and visualize results

The simulation uses a combination of time-step and event-based scheduling. The Urban Model steps forward in discrete time intervals (default 5 minutes), while individual agent actions and vehicle movements are scheduled as events.

4. Design Concepts

4.1 Basic Principles

The model is based on several key principles and theories from transportation modeling and urban systems:

1. **Mode choice theory**: The model implements a rational choice framework for mode selection, based on the concept of utility maximization (Ben-Akiva and Lerman, 1985). Agents choose their travel mode by comparing the perceived costs (including both monetary and time costs) of available options.

2. **Traffic flow theory**: The UXsim component of the model is based on kinematic wave theory and car-following models, specifically using a mesoscopic version of Newell's simplified car-following model (Newell, 2002).

3. **Induced demand**: The model incorporates the concept of induced demand, which suggests that improvements in transportation systems can lead to increased travel (Downs, 1962; Cervero, 2003).

4. **Value of Time (VOT)**: The model uses the concept of Value of Time from transportation economics to represent how agents trade off time and money in their travel decisions (Small, 2012).

5. **Dynamic User Equilibrium (DUE)**: The traffic simulation component uses a DUE approach to model route choice, reflecting the idea that travelers adjust their routes based on experienced travel times (Wardrop, 1952).

4.2 Emergence

The model is designed to reveal emergent phenomena at the system level, including:

- Modal shift patterns as a result of individual mode choices
- Traffic congestion patterns emerging from individual trip decisions and route choices
- Parking demand distribution across the urban area
- Potential unintended consequences of AV adoption, such as increased total vehicle kilometers traveled

4.3 Adaptation

Agents in the model adapt their behavior in several ways:

- Mode choice: Agents select their travel mode based on the perceived costs and available options for each trip.
- Route choice: For car and AV trips, routes are dynamically updated based on traffic conditions (implemented in the UXsim component).
- Trip chaining: Agents adapt their available modes based on their previous trips, reflecting constraints such as needing to return home with the same mode they left with.

4.4 Objectives

Agents in the model aim to minimize their perceived travel costs, which include both monetary costs and time costs weighted by their individual Value of Time. This objective is expressed in the `choice_rational_vot` method of the `Traveler` class.

4.5 Learning

The current model does not implement explicit learning mechanisms for individual agents. However, the Dynamic User Equilibrium approach in the traffic simulation component represents a form of collective learning, where the system as a whole adapts to changing conditions.

4.6 Prediction

Agents make implicit predictions about travel times and costs when choosing their mode of transport. These predictions are based on current information about the transportation network and their personal experiences (represented by their Value of Time and other parameters).

4.7 Sensing

Agents are assumed to have perfect information about: - Their own attributes (e.g., car ownership, driver's license) - Available transportation modes - Travel times and costs for different modes

The model does not currently implement limitations on sensing or information availability, which could be an area for future refinement.

4.8 Interaction

Agents interact indirectly through their impact on the transportation system: - Car and AV trips contribute to traffic congestion, affecting travel times for other agents - Vehicle parking affects the availability of parking spaces in different areas

Direct agent-to-agent interactions are not currently modeled.

4.9 Stochasticity

The model incorporates stochasticity in several ways:

- Trip generation: The number and timing of trips for each agent are determined probabilistically based on hourly trip probabilities.
- Value of Time: Each agent's Value of Time factor is drawn from a lognormal distribution.
- Initial conditions: Agent attributes like car ownership and possession of a driver's license are assigned probabilistically based on data for each postal code area.
- Traffic simulation: The UXsim component includes stochastic elements in route choice and traffic flow.
- Origin-destination pairs: Trip destinations are chosen probabilistically based on origin-destination matrices.

4.10 Collectives

The model does not explicitly represent collectives or agent groups. However, agents are implicitly grouped by their postal code and MRDH region, which influences their trip patterns and available transportation options.

4.11 Observation

The model collects and outputs various data for analysis:

- Mode choice distribution (overall and distance-weighted)
- Trips by mode and time of day
- Traffic conditions (from UXsim), including speed, density, and flow
- Parking demand by area over time
- Journey details for each completed trip, including origin, destination, mode, travel time, and costs
- System-level metrics such as total vehicle kilometers traveled, average speeds, and congestion levels

This data is saved in various formats (Python pickle files, Feather files) for further analysis and visualization.

5. Initialization

The model is initialized with the following steps:

1. Set up the simulation environment with specified parameters (e.g., number of agents, start and end times, time step, policy variables).
2. Load geographical and population data for the Rotterdam area from various sources (CBS, MRDH, OpenStreetMap).
3. Create agents and assign them to postal code areas based on population distribution.
4. Assign car ownership and driver's licenses to agents based on data for each postal code.
5. Generate trip schedules for each agent based on time-of-day probabilities.
6. Initialize the UXsim traffic simulation component with the road network data.
7. Set up initial parking distribution based on car ownership in each area.
8. Initialize data collection structures for various metrics.

The initial state can vary between simulation runs due to the stochastic elements in agent creation, attribute assignment, and trip generation.

6. Input data

The model uses several external data sources as input for agent and system behavior:

6.1 Population data by 4-digit postal code (PC4) from CBS

Population data from the CBS is used to distribute agents across the urban area (CBS-postcode). The Dutch 4-digit postal code areas are used, which roughly represent a neighbourhood each. This gives heterogeneity in the system and enables adequate travel counts and traffic pressure on the network. In the 125 PC4 areas, there are in total 991,575 residents. The population in each area gets scaled down with the platoon size (10 by default), resulting in approximately 100,000 agents in the simulation.

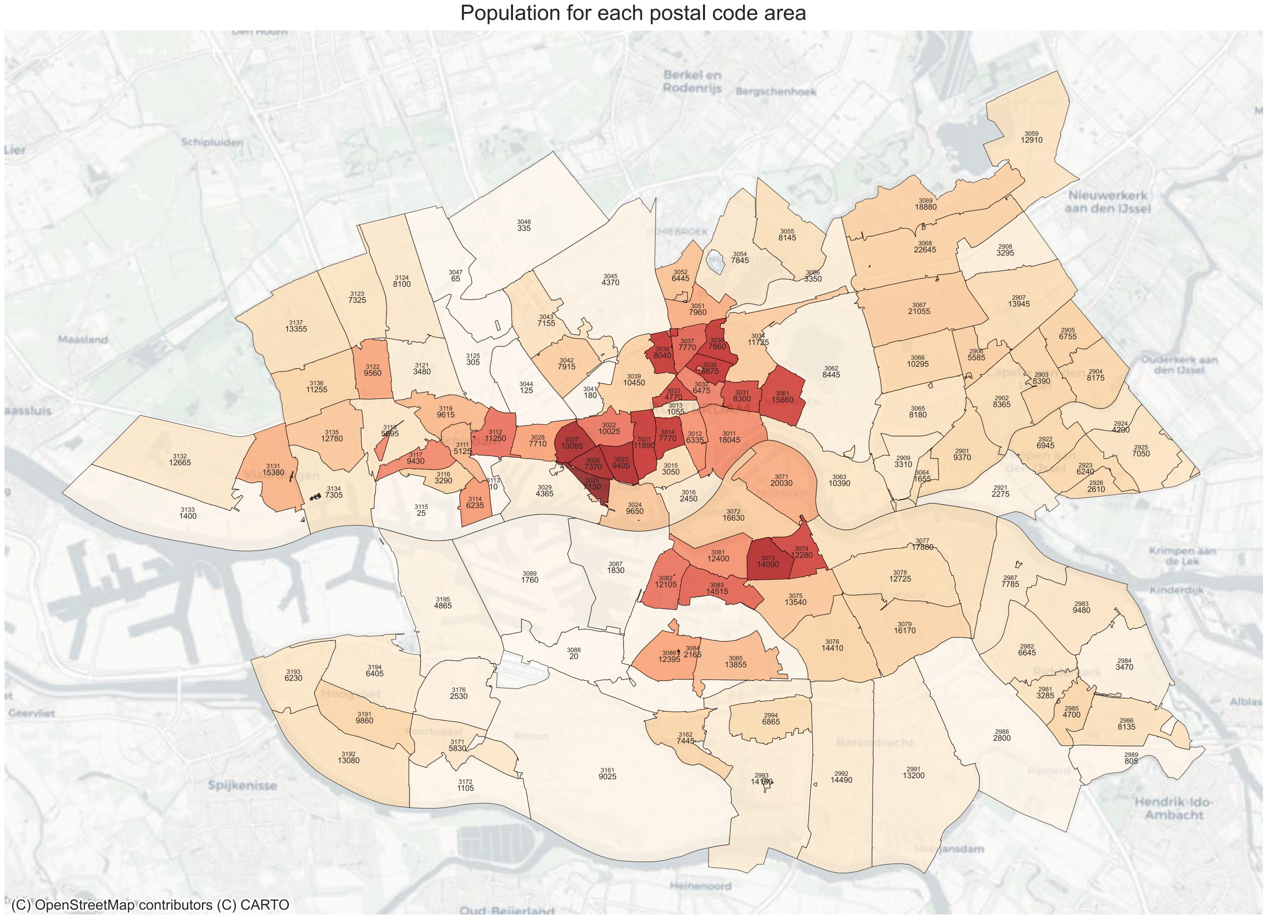

Fig A.1: Population count for each PC4 area (number) and population density (color)

6.2 Car ownership and driver's license data by postal code (CBS)

Car ownership is also sourced from the CBS per PC4 area. For each area, a certain percentage of agents gets assigned a car as additional available mode. On average that's 35.4% and varies between ~19% and ~65% per area. This enables heterogeneity among agents and enables realistic mode choices.

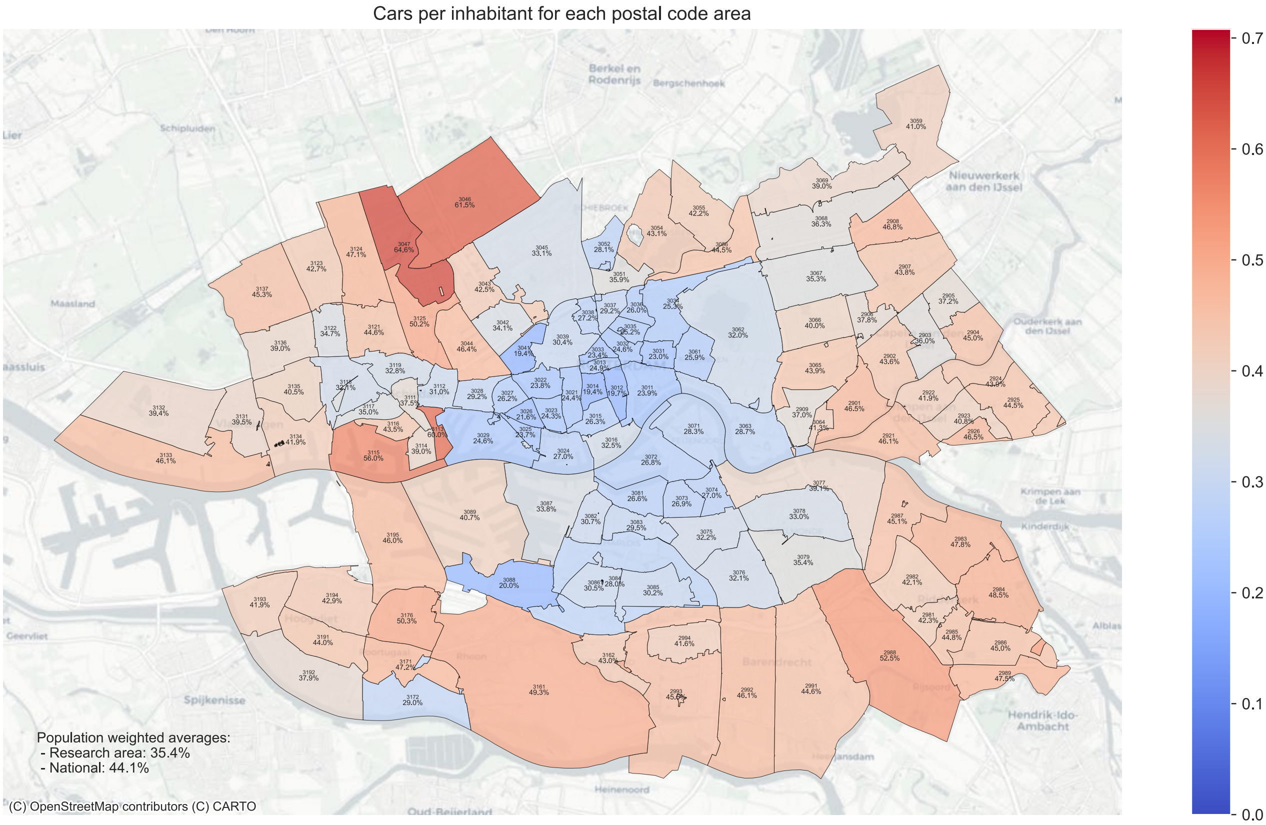

Fig A.2: Car ownership per inhabitant for each PC4 area

The full analysis for both the population and car ownership data is available in the *prototyping/pc4.ipynb* notebook.

6.3 Road network data from OpenStreetMap

The road network data was extracted from OpenStreetMap (OSM) using the OSMnx library (version 2.0.0b2) on September 30, 2024. The network consists of two distinct components: a detailed inner-city network covering the city area and a broader surrounding network covering supporting area. This dual-network approach allows for higher resolution within the primary study area while still allowing traffic to flow in and out of the city.

The inner-city network includes all roads from tertiary level and above (motorways, trunks, primary, secondary, and tertiary roads, including their respective link roads), which are all arterial roads to allow traffic to flow accurately. The surrounding network includes only major roads (secondary level and above) to reduce computational complexity, since precise traffic flow is less critical in these areas (and are not included in the measurements). Roads under construction, particularly the new A16 motorway and Blankenburg tunnel, were included to ensure the network represents the near-future situation.

The downloaded networks contained: - City network: 44,464 nodes and 56,236 edges - Supporting network: 48,674 nodes and 57,024 edges - Combined raw network: 93,138 nodes and 113,260 edges

Since the computational complexity scales quadratically with the number of edges, the raw networks were simplified to reduce the number of nodes and edges. This was done by eliminating nodes with degree 2, which are not intersections, and consolidating intersections within a certain distance threshold.

These networks were processed through the following steps: 1. Projection to a unified coordinate reference system (EPSG:28992, Amersfoort / RD New) 2. Network attribute assignment, including: - Speed limits (derived from OSM maxspeed tags) - Number of lanes (from OSM lane tags) - Road type classification - Network identification (city or surrounding area) 3. Intersection consolidation using variable tolerances: - 10-meter tolerance for the city network - 50-meter tolerance for the surrounding network 4. Network simplification while preserving essential attributes (length, travel time, lanes)

The final processed network contains 1,575 nodes and 3,328 edges, which was both suitable for the research problem and feasible to simulate. Each edge in the network contains the following key attributes: - Length (meters) - Speed limit (km/h) - Number of lanes - Road type (motorway, trunk, primary, secondary, tertiary) - Network identification (city or surrounding) - Travel time (seconds, calculated from length and speed limit)

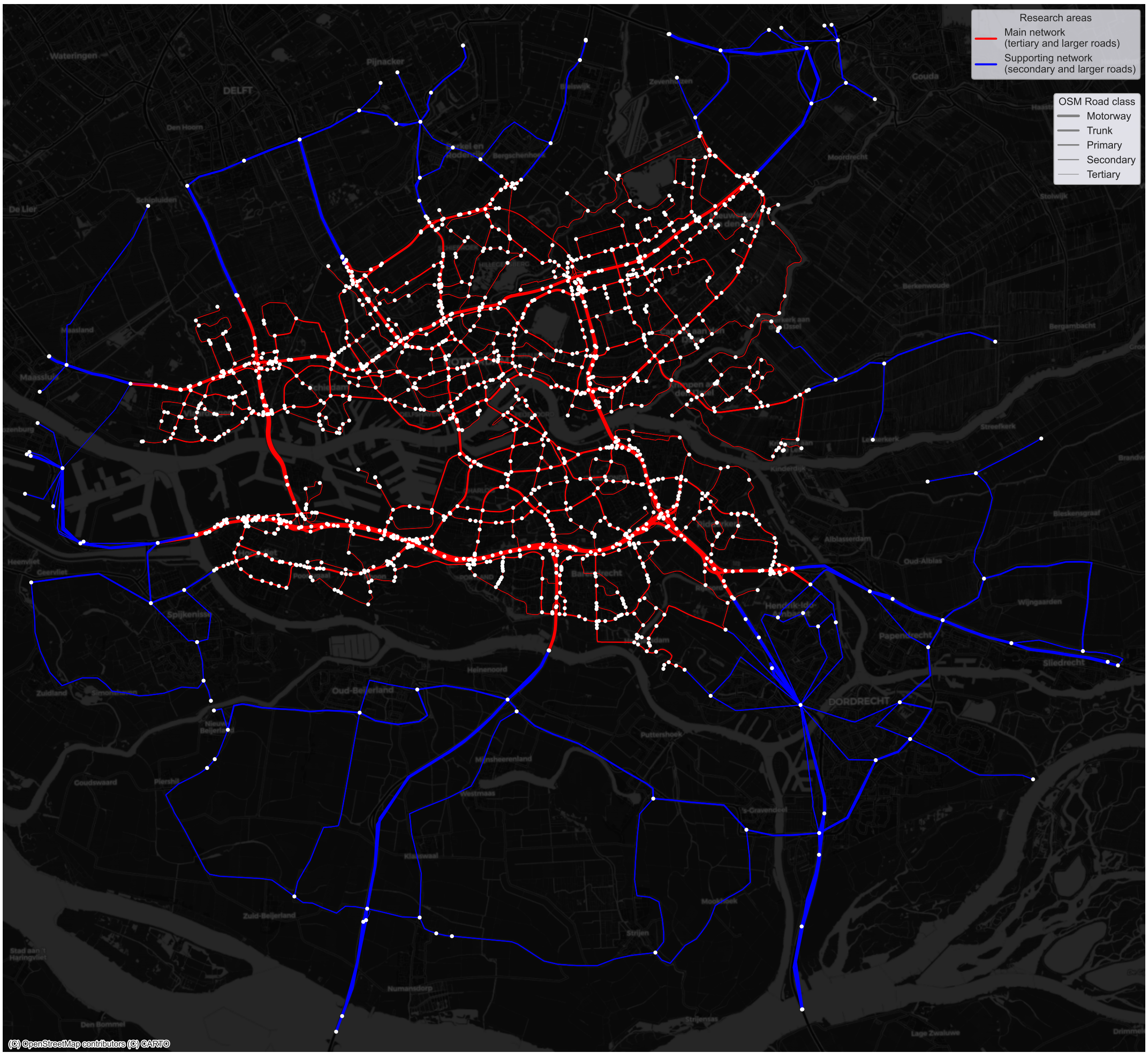

Fig A.3: The processed road network showing hierarchical road types (line width) and network components (color). The main network (red) includes tertiary and larger roads within Rotterdam, while the supporting network (blue) includes secondary and larger roads in the surrounding area.

During simulation, the network is used by the UXsim traffic model to: - Calculate shortest paths between origins and destinations - Simulate traffic flow and congestion - Track vehicle movements and area-based metrics - Apply speed reductions in policy scenarios

The simplified network structure proved particularly efficient for the mesoscopic simulation approach, allowing for city-scale simulations while maintaining adequate detail for analyzing both local and system-wide effects of autonomous vehicles and policy interventions.

The full analysis is available in the *network/create_network.ipynb* notebook.

6.4 Travel time and distance data for public transit and cycling (from Google Maps API)

Travel times and distances for non-car modes (public transit and cycling) were collected using the Google Maps Distance Matrix API. Data was gathered for all possible origin-destination pairs between the 125 postal code areas in the Rotterdam urban area, resulting in 15,500 unique combinations for both cycling and public transit. This fell withing the free tier of the API, which allows for up to 40.000 elements travel time requests per month, costing $156.25 for the complete matrix in both modes, within the $200 free monthly credit Google provides.

The data collection was performed for Thursday, September 17, 2024, at 08:00, representing typical weekday conditions. While for bycicle the travel time is relatively stable, for public transit it can vary due to the frequency of the services and more data collections would be needed to capture proper early morning, late evening and weekend travel times. The travel times on a Thursday morning are when the highest frequency of trips are made, and provide generally the fastest travel times, representing the optimal conditions for public transit.

The API provided both travel time (in seconds) and distance (in meters) for each origin-destination pair. For transit, this includes walking to/from stops, waiting times, and any transfers. For cycling, it assumes use of the standard cycling infrastructure and average cycling speeds.

Centroid-to-centroid measurements between postal code areas where made, initially only between the 21 MRDH regions (420 pairs), which lead to visible noise in even the high-level KPIs. It also didn't allow within-region travel, which is a significant part of the trips. Also, some of the centroids were really unfortunately placed (right between stations for example), which with the low number of points resulted in unexpected behavior. Therefore, the resolution was increased to 4-digit postal code level, and OD lookup tables for all 15.500 pairs between the geographical centroids of the 125 PC4 areas was created. This directly lead to practically eliminating the noise in the KPIs, and allowed for trips to other PC4 areas within the same MRDH region.

To validate and gain insights into the collected data, an exploratory analysis was performed, including histograms, box plots, and scatter plots of travel times and distances for both modes. Notably:

Fig A.4 shows the distribution of cycling travel times are more skewed towards shorter durations, with a median and mean below 40 minutes, while transit travel times were more evenly distributed, with a median and mean above 50 minutes.

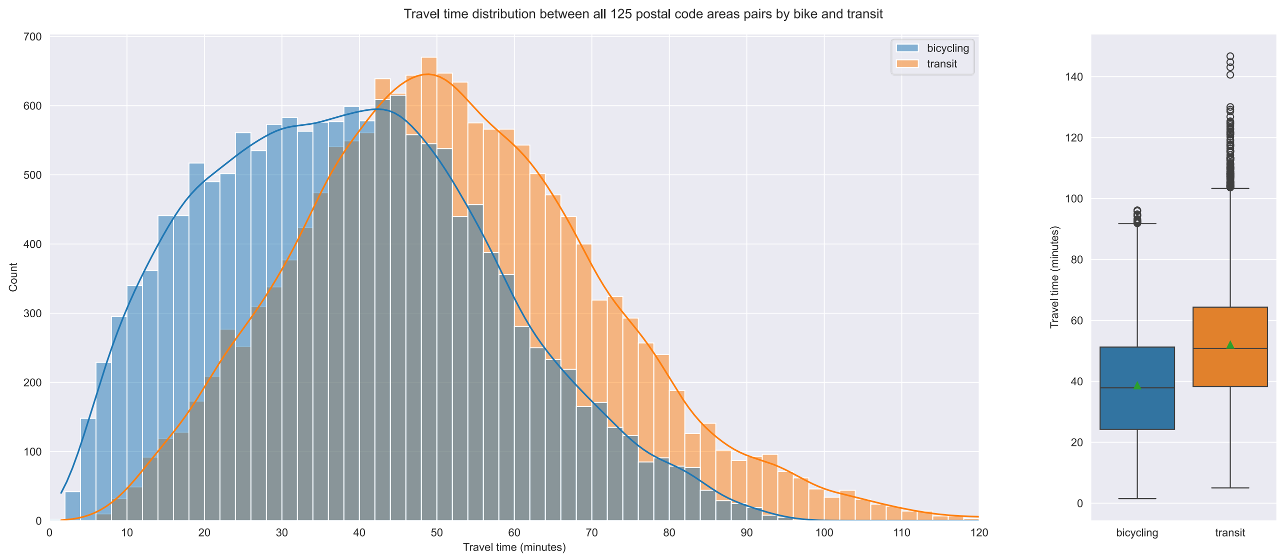

Fig A.4: Distribution of travel times between the 15.500 centroid-pairs for cycling and public transit.

Fig A.5 shows a scatter plot of travel times versus bird's-eye distances for both modes. It shows cycling having a clear maximum speed and relatively linear relationship between time and distance, while public transit has a lesser correlation, with a lot of variation in travel times for similar distances, and now clear minimum or maximum speeds.

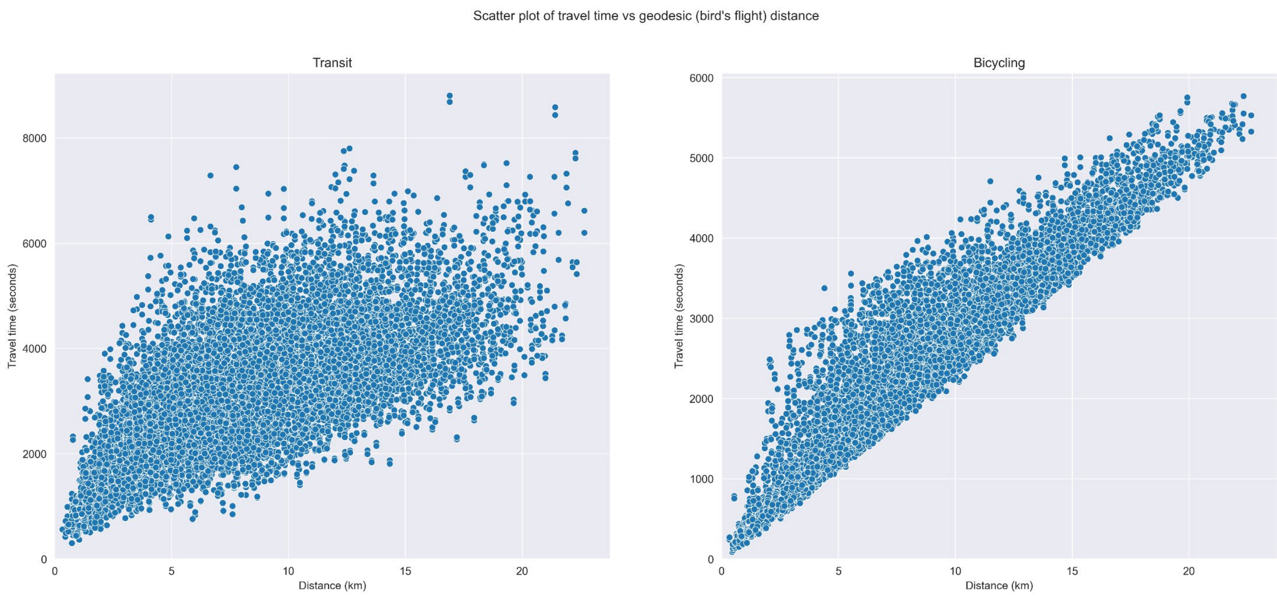

Fig A.5: Scatter plot of travel times versus distances between the 15.500 centroid-pairs for cycling and public transit.

The full analysis is available in the *travel_api/travel_time_distance_google.ipynb* notebook.

6.5 Trip generation probabilities by hour (derived from ODiN 2023 data)

Trip generation probabilities were derived from the Dutch National Travel Survey (ODiN) 2023 dataset to create temporal patterns of travel demand. The ODiN survey provides detailed information about travel behavior in the Netherlands, including the timing of trip starts throughout the day. Since it is a survey, the data is not perfect, and more care was taken to ensure the data was cleaned properly and representative for this research.

While ODiN offers a wealth of data, the focus was on the timing of trips, which was used to create hourly trip generation probabilities for the simulation model. The data was aggregated to count the number of trips starting in each hour of the day, resulting in a distribution of travel demand over time.

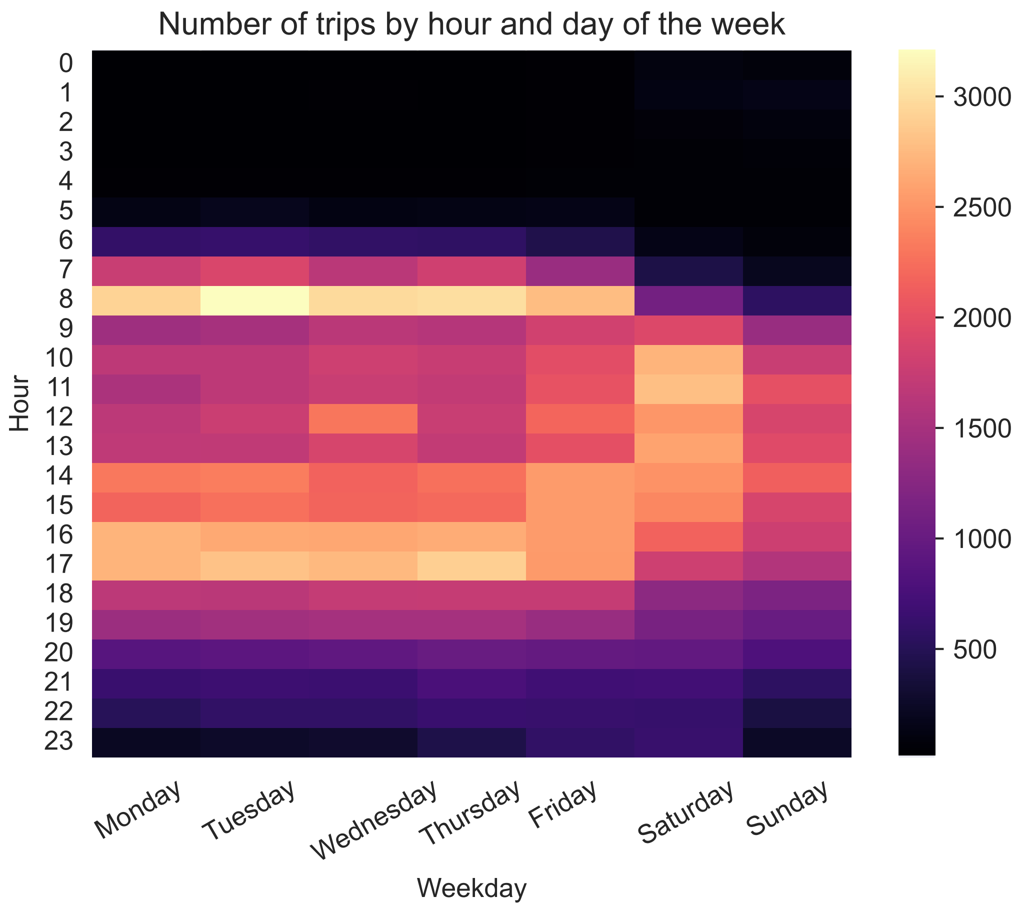

Fig A.6: Heatmap showing the number of trips by hour and day of the week. The color intensity indicates the number of trips, with lighter colors representing more trips.

The heatmap in Figure A.6 shows several distinct temporal patterns: - A sharp morning peak (8:00-9:00) and more spread out evening peak (16:00-18:00) peak hours on weekdays - Lower (especially on Sunday) but more spread out travel demand during weekends - Very low travel activity between midnight and 5:00 - Relatively consistent patterns Monday through Thursday (except with a small lunch peak on Wednesday, probably due to school schedules) - Slightly different pattern on Fridays, with a less pronounced evening peak, more spread out through the afternoon - Weekend travel starting later in the day and more evenly distributed

For use in the simulation model, the trip generation probabilities were calculated by: 1. Counting the number of unique travelers per day of the week 2. Counting trips starting in each hour 3. Dividing the hourly trip counts by the number of unique travelers to get the probability that an individual starts a trip in that hour 4. Averaging the probabilities for Monday through Thursday to get representative weekday patterns (done in the Model itself, any day or combination of days can be selected there).

Since there are relatively large steps between some hours, 15-minute intervals were also explored to see if more smoother steps could be achieved.

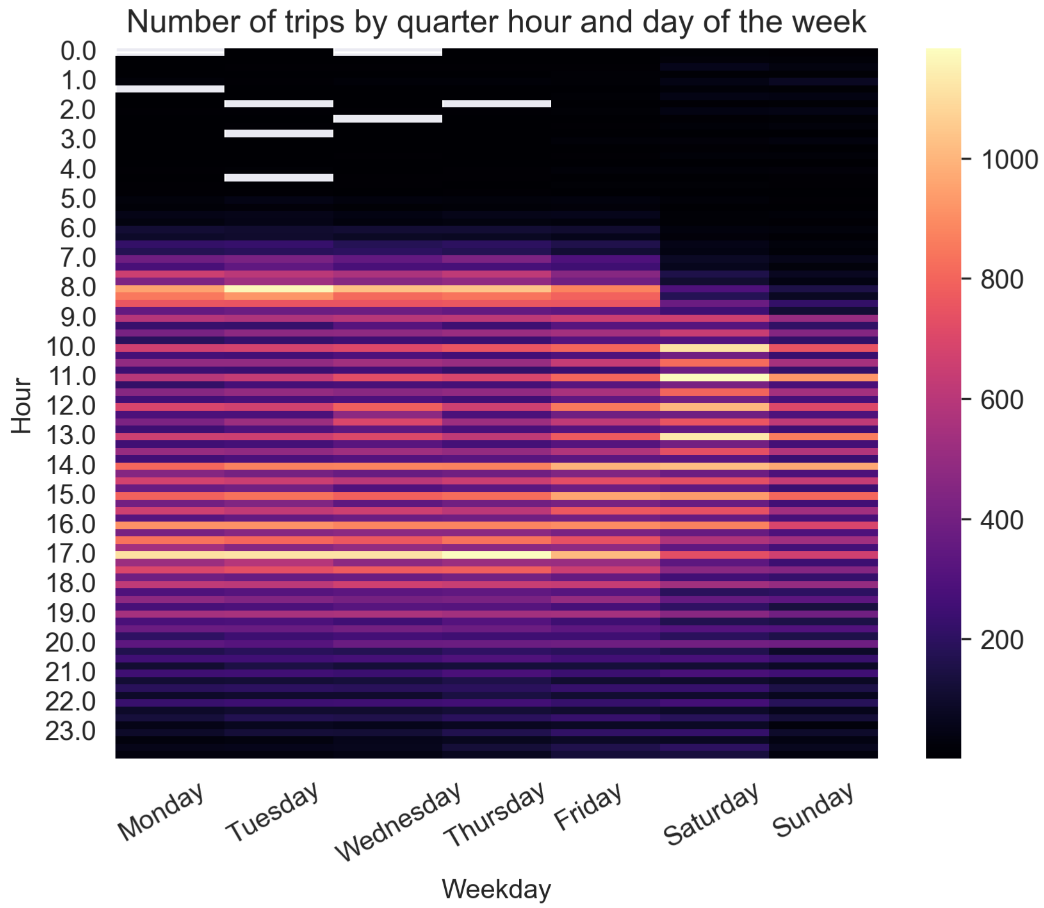

Fig A.7: Heatmap showing the number of trips by quarter-hour and day of the week.

However, as can be seen in the quarter-hour heatmap, there are very distinct pattern in which the whole, and in a lesser extent half, hours are over-represented. This is likely caused by people rounding their travel times to the nearest hour in the survey, and the data was therefore kept in hourly bins.

As a default value the travel distribution is averaged over Monday to Thursday, as weekdays are when the largest congestion and travel demand is expected, and thus most interesting for this research. The number of trip for each hour of each day was normalized over the number of the number of people taking trips that day, to create a lookup table giving the probability of a person starting trip starting in a specific hour of a specific day.

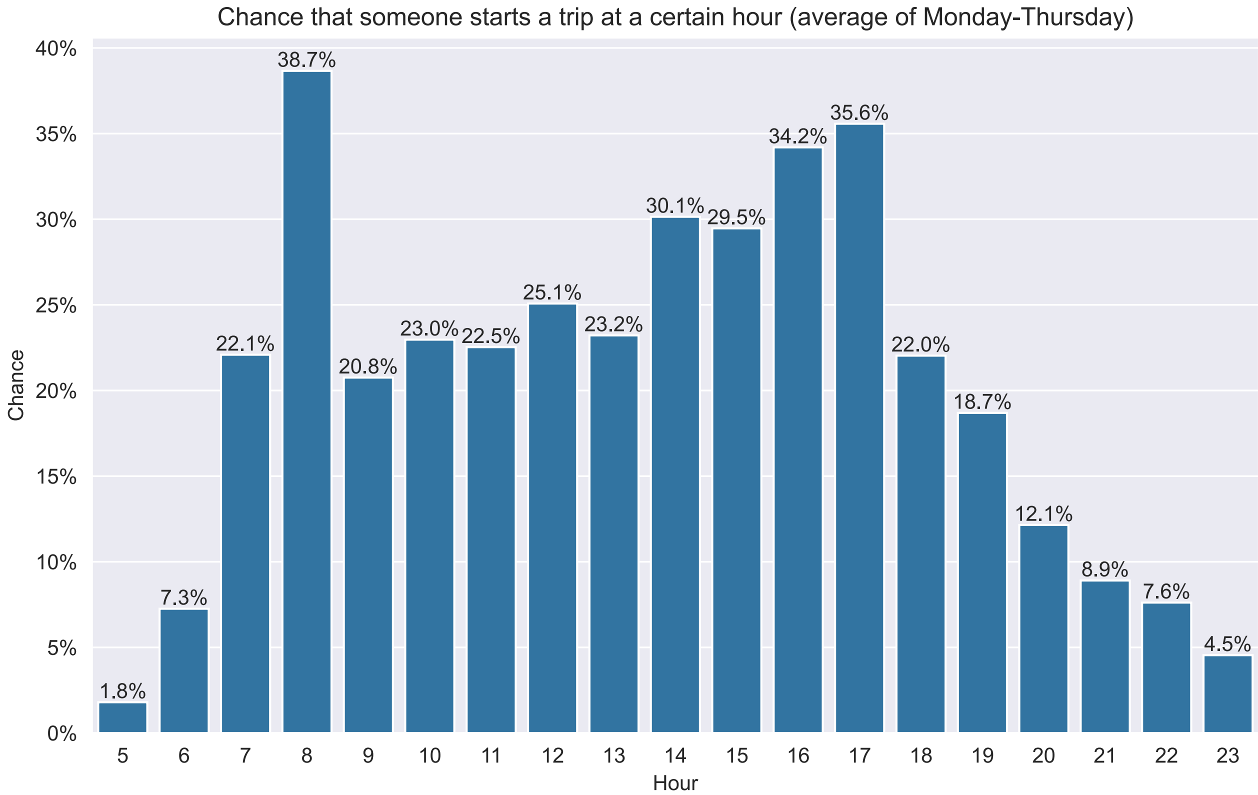

Fig A.8: Average probability of an individual starting a trip by hour during weekdays (Monday-Thursday).

Using these lookup tables, the start time, end time (and thus duration) and day of the week could be varied in the model, while always initiating a representative number of trips. Many initial tests were only performed on a few hours (like 7:00-11:00), while the full 05:00-24:00 in which significant travel demand is present was used for all experiments.

The full analysis is available in the `prototyping/ODiN_analysis.ipynb` notebook.

6.6 Origin-destination matrices for the Rotterdam area (V-MRDH model)

Origin-destination (OD) matrices were obtained from the V-MRDH 3.0 transport model (October 2023 version), which provides detailed travel demand data for the Rotterdam-The Hague metropolitan area. The V-MRDH model divides The Netherlands into 65 traffic analysis zones with varying sizes - smaller zones in dense urban areas and larger zones in peripheral regions. This model was selected because it: - Provides validated OD patterns based on extensive traffic counts and travel surveys - Captures different time periods (morning peak 7-9h, evening peak 16-18h, and off-peak) - Contains separate matrices for different transport modes (car, bicycle, public transport) - Covers both internal traffic within Rotterdam and external traffic to/from surrounding areas

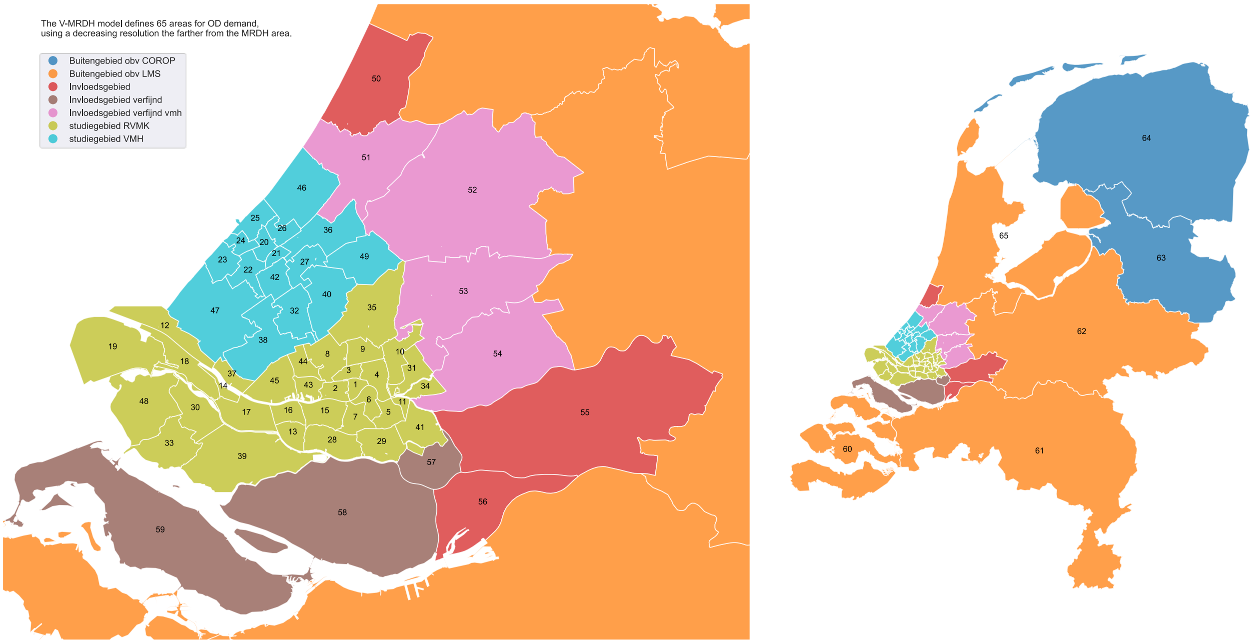

Fig A.9: The 65 traffic analysis zones defined in the V-MRDH model, with decreasing resolution farther from the MRDH area. Numbers indicate zone identifiers.

The OD matrices were processed in several steps:

1. Data extraction and normalization:
    - Raw matrices were extracted for each mode and time period
    - Values were normalized to create probability distributions for each origin zone
    - Total travel demand was preserved while converting absolute numbers to relative flows
2. Area selection and filtering:
    - 21 zones covering the Rotterdam city area were selected as internal zones
    - 13 surrounding zones were designated as external zones for modeling boundary traffic
    - Remaining peripheral zones were excluded from the simulation
3. Creation of lookup tables:
    - Probability matrices were created for trip distribution in different time periods
    - Separate tables were made for internal-internal and internal-external flows
    - Data was stored in efficient dictionary format for quick runtime lookup

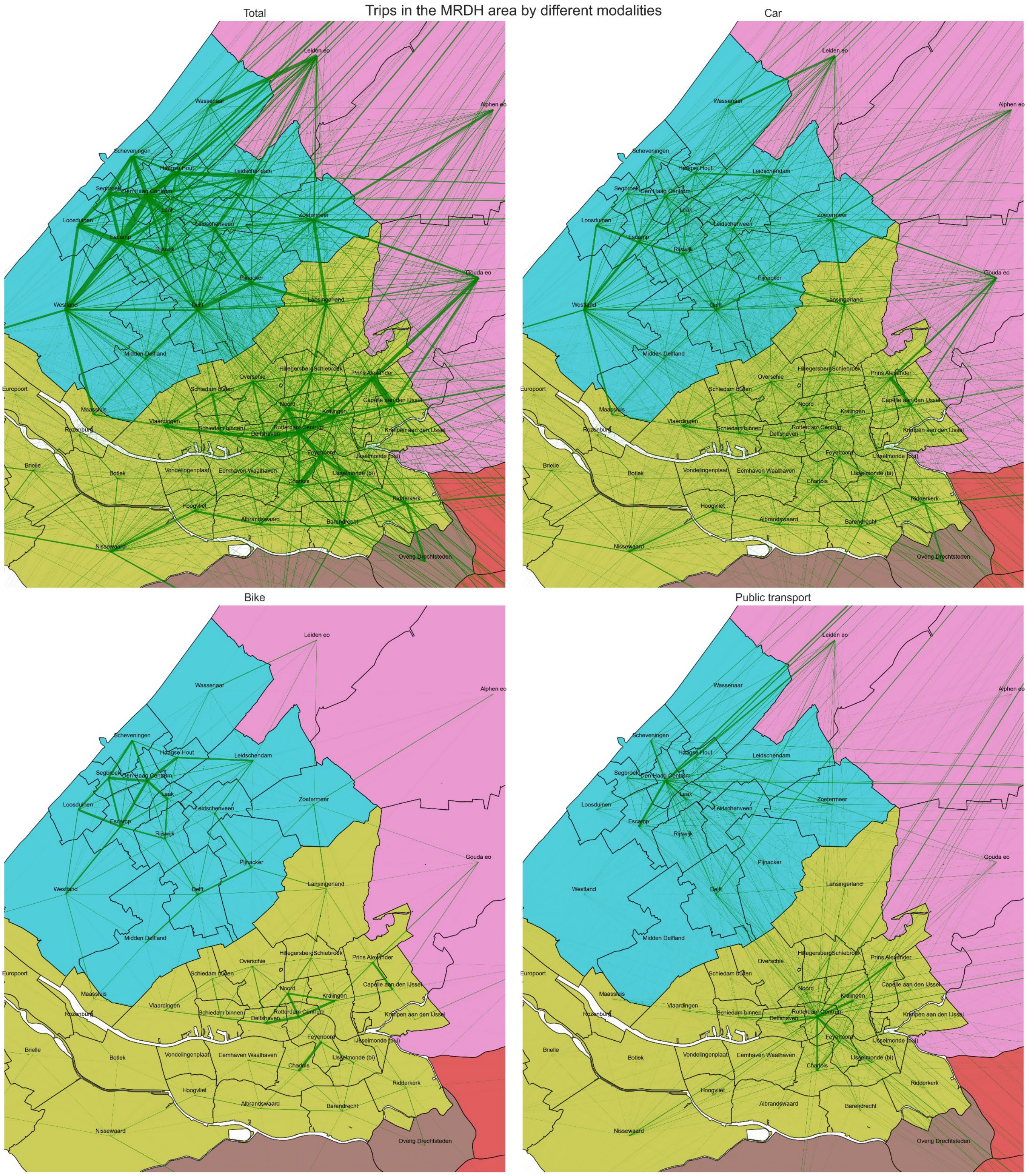

Fig A.10: Travel demand visualization by mode (total, car, bicycle, public transport) between zones in the Rotterdam area. Line thickness indicates trip volume.

The matrices revealed several interesting patterns, used for both model validation and input:

First, the modal split varies significantly by area. In the inner Rotterdam area (Noord, Kralingen, Rotterdam Centrum, Feyenoord, Delfshaven), the model split was 13.4% car, 69.9% bicycle and 16.7% public transport. In the (full study area) of broader Rotterdam, the split was 37.7% car, 49.0% bicycle and 13.3% public transport. These modal splits were used to validate and kalibrate the model.

Secondly, distinct time-of-day patterns were present, as shown in the figure below.

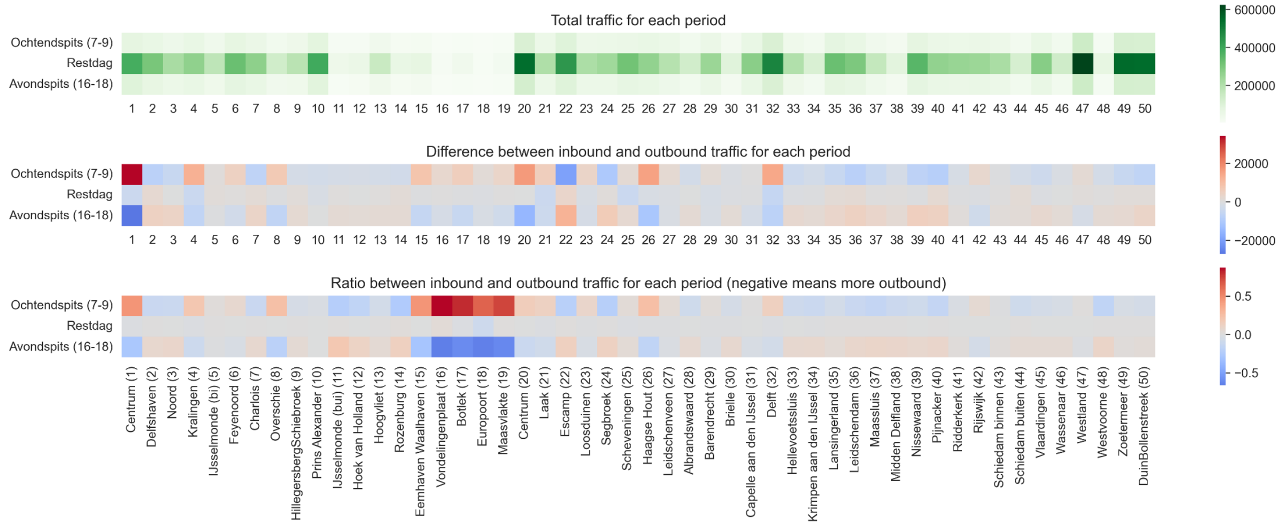

Fig A.12: Analysis of inbound/outbound traffic patterns. Top: total traffic volume. Middle: absolute difference between inbound and outbound flows. Bottom: relative asymmetry ratio.

Certain regions showed strong inbound or outbound flows during morning and evening peak hours. For example, the city center (Rotterdam Centrum) had a high volume of inbound traffic in the morning and outbound traffic in the evening, reflecting commuting patterns. The industrial harbor area (Botlek, Europoort, Maasvlakte and Vondelingenplaat) had a similar pattern, with especially the ratio of inbound to outbound traffic being high. Evening peak displays opposite outbound patterns, while off-peak hours have more balanced bi-directional flows.

From this data, OD chance dictionaries were created for each of the three time periods (morning peak, evening peak, off-peak). For each origin, the probability of traveling to each destination was stored, allowing for efficient lookup during trip generation. The total summed values for all modalities were used, leaving the mode choice to the agent behavior model.

Where withing the study area all internal trips were analyzed, for trips between the study area and the supporting area only the car trips were modelled. From the OD matrices, a fixed amount of cars was added to the simulation from each external zone to the internal zones and visa versa. The total daily external traffic, together with the internal demand, is shown in the figure below.

Internal total demand and external car traffic in the research area

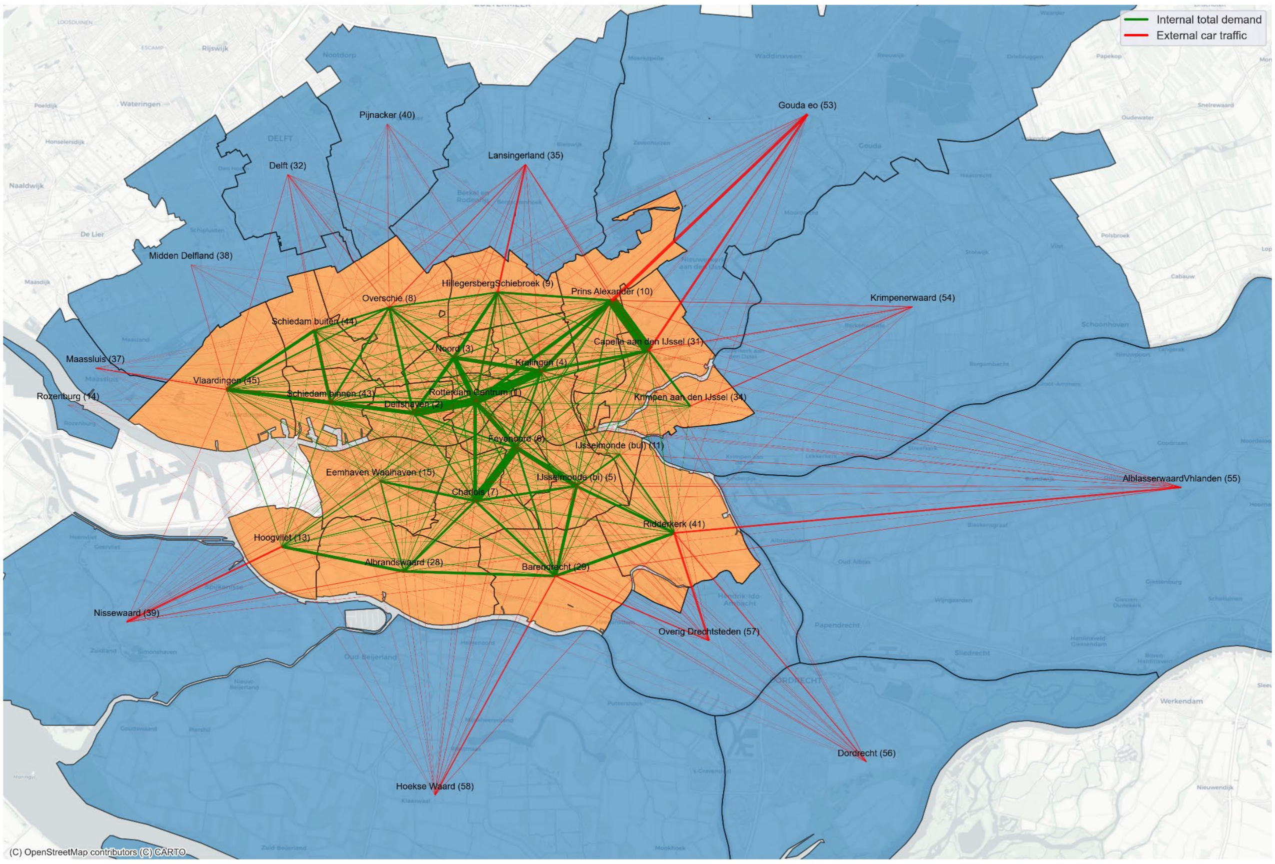

Fig A.13: Comparison of internal demand (green) and external car traffic (red) patterns.

Notable is large external traffic from the directly neighboring zones, especially from the east and south.

Finally, the processed OD data serves three main purposes in the model:

1. Trip distribution: When agents generate trips, destinations are selected probabilistically based on the normalized OD matrices for the appropriate time period.
2. External traffic: Car traffic entering and leaving the study area is simulated based on the external zone matrices, scaled by time-of-day factors.
3. Validation: The modal split and spatial distribution patterns provide reference values for validating model behavior.

One limitation is that the matrices represent current travel patterns, which may not fully reflect behavior in future scenarios with autonomous vehicles. However, they provide a validated baseline for trip distribution patterns, while mode choice is handled separately by the agent behavior model. This is in line with the short to medium term scope of this research.

The full analysis is available in the `v_mrdh/v_mrdh_od_demand.ipynb` notebook.

6.8 Value of Time data

The model uses Value of Time (VoT) data from the Dutch Institute for Transport Policy Analysis (KiM)'s 2023 study on travel time valuation (KiM-valuation). Default values per mode were set at: - Car: €10.42 per hour - Bicycle: €10.39 per hour - Public Transit: €7.12 per hour - Autonomous Vehicle: Scaled from car VoT using the av_vot_factor parameter. Experimental values of 1.0, 0.5, and 0.25 were used, resulting in the following VoT values: - AV VoT factor 1.0: €10.42 per hour - AV VoT factor 0.5: €5.21 per hour - AV VoT factor 0.25: €2.61 per hour

To capture heterogeneity in how individuals value their time, each agent's personal value of time is drawn from a lognormal distribution with parameters μ = -0.1116 and σ = 0.4724, capped at 4 times the default value. These parameters were chosen to produce a distribution with: - Mean of 1.0 (preserving the base VoT values on average) - Standard deviation of 0.5 (representing reasonable variation between individuals) - Maximum of 4.0 (preventing extreme outliers)

The resulting distribution is shown in Figure A.x:

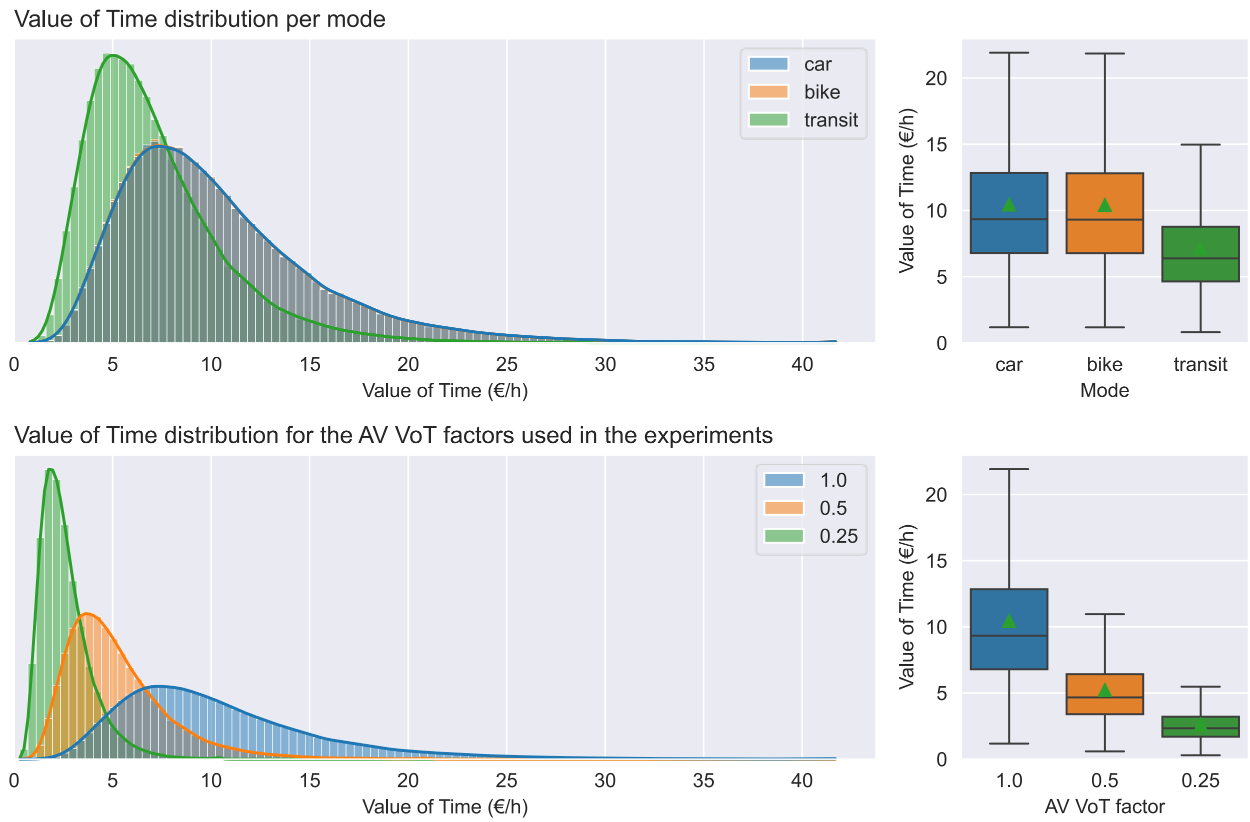

Fig A.14: Distribution of agents' Value of Time factors.

An agent's final VoT for each mode is calculated by multiplying the mode's default value by their personal VoT factor. For example, an agent with a VoT factor of 1.5 would value car travel at €15.63 per hour (1.5 × €10.42). This heterogeneous valuation leads to varied mode choices among agents even when faced with identical travel options.

Note that the VoT factor is consistent for all modes, meaning that an agent who values their time highly for car travel will also value their time highly for other modes.

For autonomous vehicles, an additional `av_vot_factor` parameter scales the car VoT before applying the agent's personal factor. This represents potential differences in how time is valued in AVs compared to conventional cars, for example due to the ability to engage in other activities while traveling. The av_vot_factor is one of the key uncertainties explored in the scenario analysis.

All VoT values are converted from euros per hour to euros per second in the model for computational efficiency, since travel times are tracked in seconds. The values represent 2022 price levels and include VAT, following standard Dutch transportation analysis practice.

This implementation of heterogeneous Values of Time helps capture realistic variation in travel preferences and mode choices among agents. It also prevents hard tipping points in mode choice, where small changes in travel times or costs could lead to large shifts in behavior.

6.9 Data storage, preprocessing, and integration

The model integrates multiple data sources through a centralized *Data* class in *data.py*, which is initialized once at model startup and made available throughout the simulation. This section describes how different data sources are processed and utilized within the model.

The following key data structures are loaded and processed during model initialization:

1. **Travel time and distance data**
   - Stored in pickle files: *travel_time_distance_google_{mode}.pkl* and *travel_time_distance_google_{mode}_pc4.pkl*
   - Available for modes: "transit" and "bicycling"
   - Contains matrices of travel times and distances between origins and destinations
   - Distances are converted from meters to kilometers during loading
   - Used by agents to determine travel times and costs for non-car modes
2. **Geographic information**
   - Loaded from *polygons.pkl*
   - Contains three key polygons: city_polygon, area_polygon, autoluw_polygon
   - Converted to GeoSeries with EPSG:28992 projection
   - Used for spatial queries and policy implementation zones
3. **Population and area data**
   - Population data: *population_data_pc4_65coded.pkl*
   - Areas data: *areas_mrdh_weighted_centroids.pkl*
   - Various mapping dictionaries maintained for cross-referencing:
     - *mrdh65_to_name*: Maps region numbers to names
     - *pc4_to_mrdh65*: Maps postal codes to MRDH regions
     - *mrdh65_to_pc4*: Maps MRDH regions to lists of postal codes
4. **Car ownership and licenses**
   - Stored in *rijbewijzen_personenautos.pkl*
   - Contains car ownership and driver's license rates by postal code
   - Used to assign cars and licenses to agents based on their location
5. **Trip generation data**
   - Trip probabilities: *trips_by_hour_chances.pickle*
   - Trip count distribution: *trip_counts_distribution.pickle*
   - Used to generate realistic temporal patterns of trip starts
6. **Origin-destination matrices**
   - Stored in *od_chance_dicts_periods.pickle*
   - Contains matrices for different time periods (morning peak, evening peak, off-peak)
   - Used to determine trip destinations based on origins

Several data transformations are performed during initialization, the most notable:

1. **Geographic filtering**
   - Centroids are calculated for both postal codes and MRDH65 regions
   - Areas are classified as “in_city”, “in_area”, or “autoluw” based on polygon containment
   - Limited to populated areas within the city (21 specific MRDH65 regions)
2. **Origin-destination processing**
   - OD matrices are normalized to create probability distributions
   - Destinations outside the study area are assigned zero probability
   - Same-location trips are handled specially based on area size
   - Probabilities are renormalized after filtering
3. **Travel time data**
   - Conversions from raw units to model units (meters to kilometers, etc.)
   - Creation of lookup dictionaries for efficient runtime access
   - Validation of data completeness for all required origin-destination pairs

A trade-off was made here between pre-processing data for efficiency and maintaining flexibility for future extensions. While much data was pre-processed to reduce runtime overhead, some of the more destructive processing (like selecting and aggregating) was done on data initialization, to allow for easy modification and extension of the model, without needed to alter data files themselves.

7. Submodels

Aside from the two main submodels for mode-choice and traffic simulation discussed in section 3.2, the model has several smaller submodels that handle specific aspects of the simulation.

7.1 Trip Generation

Trips are generated for each agent using the following process:

1. For each hour in the simulation period, generate a trip with probability given by *trips_by_hour_chance*.
2. Ensure an even number of trips by potentially adding or removing a trip.
3. Assign destinations based on origin-destination probability matrices, differentiating between peak and off-peak hours.
4. Schedule the trips as events in the simulation.

7.2 Mode Choice

The mode choice model is implemented in the *choice_rational_vot* method of the *Traveler* class. It calculates the perceived cost for each available mode:

```
perceived_cost = monetary_cost + travel_time * value_of_time[mode]
comf_perceived_cost = perceived_cost * comfort_factor[mode]
```

The mode with the lowest comfort-adjusted perceived cost is chosen.

7.3 Traffic Simulation

The traffic simulation uses UXsim, a mesoscopic traffic simulator that implements a version of Newell’s simplified car-following model. This model represents traffic flow as a kinematic wave, a state between microscopic (individual vehicle) and macroscopic (flow-based) modeling, providing computational efficiency while maintaining key traffic dynamics and the ability to measure traffic and congestion on a link or area level.

The driving behavior of a platoon consisting of Δn vehicles in a link is expressed as:

$$X(t + \Delta t, n) = \min\{X(t, n) + u\Delta t, X(t + \Delta t - \tau\Delta n, n - \Delta n) - \delta\Delta n\}$$

where $X(t, n)$ denotes the position of platoon n at time t, Δt denotes the simulation time step width, u denotes free-flow speed of the link, and δ denotes jam spacing of the link. This equation represents vehicles traveling at free-flow speed when unconstrained, while maintaining safe following distances when in congestion.

Traffic behavior at intersections is handled by the incremental node model, which resolves conflicts between competing flows by processing vehicles sequentially based on predefined merge priorities. This approach maintains consistency with the kinematic wave model while efficiently managing complex intersection dynamics. The OpenStreetMap data didn't contain explicit intersection information, merge priorities were left at their default values, giving each incoming lane equal priority.

For route choice, UXsim employs a Dynamic User Optimum (DUO) model with stochasticity and delay. The attractiveness $B_o^{z,i}$ of link o for vehicles with destination z at time step i is updated as:

$$B_o^{z,i} = (1 - \lambda)B_o^{z,i-\Delta i_B} + \lambda b_o^{z,i}$$

where λ is a weight parameter and $b_o^{z,i}$ indicates whether link o is on the shortest path to destination z. This formulation allows vehicles to gradually adapt their routes based on evolving traffic conditions, rather than instantly responding to changes in travel times.

Road characteristics are captured through differentiated jam density parameters based on road hierarchy, with motorways having lower jam densities (0.14 vehicles/meter/lane) than local streets (0.20 vehicles/meter/lane). This reflects the different spacing requirements at different operational speeds and road types. Each link's behavior is governed by a triangular fundamental diagram that relates traffic flow to density, characterized by the free-flow speed, jam density, and resulting capacity.

The model uses a hybrid simulation approach: Mesa's discrete event simulation manages agent decisions and scheduling, while UXsim handles continuous traffic flow dynamics. Synchronization between the two systems occurs at 5-minute intervals, where agents make mode choices based on current network conditions, new vehicle trips are added to UXsim, traffic flow is simulated, and the updated network conditions inform future agent decisions. Network performance data is collected at 15-minute intervals using UXsim's area-based analysis capabilities, allowing for evaluation of both localized congestion effects and network-wide performance metrics.

7.4 Parking

Parking is modeled by tracking the number of parked vehicles in each MRDH region:

- When a car trip starts, a parking space is freed in the origin area.
- When a car trip ends, a parking space is occupied in the destination area.

The *parked_per_area* dictionary is updated in real-time, and the *parked_dict* stores the parking situation over time for later analysis.

7.5 Cost Calculation

Travel costs are calculated differently for each mode:

- Car: Distance-based cost using a fixed price per kilometer
  - *distance * car_price_per_km_variable*
- AV: Initial cost plus distance and time-based costs
  - *av_initial_costs + distance * av_costs_per_km + travel_time * av_costs_per_sec*
- Bike: Assumed to be zero
- Transit: Distance-based cost with a non-linear pricing scheme, simulating real-world transit pricing:

```
ranges = [(40, 1), (80, .979), (100, .8702), (120, .7),
          (150, .48), (200, .4), (250, .15), (float('inf'), 0)]
```

  - In practice, the vast majority of trips are under 40 kilometers, and thus priced at the full rate, but this allows to extend the model further.

7.6 Value of Time

Each agent's Value of Time is calculated as:

```
vot_factor = min(np.random.lognormal(mean=-0.1116, sigma=0.4724), 4)
value_of_time = {mode: default_vot[mode] * vot_factor for mode in modes}
```

This creates heterogeneity in how agents value their time, influencing their mode choices. It prevents sharp tipping points in mode choice and allows for more realistic variation in travel preferences. For more details and sources, see the Value of Time data section.

7.7 External Vehicle Load

External vehicle traffic is modeled based on origin-destination matrices:

- Vehicles are added at the start of each hour based on time-of-day probabilities.
- The number of vehicles is scaled by *ext_vehicle_load* factor.
- Origins and destinations are chosen from predefined external and internal areas.

7.8 Scenario & Policy Implementation

The model includes several scenario uncertainties and policy levers that can be adjusted:

Scenario uncertainties

1. AV cost factor: Scales the fixed, time based and distance based cost of using autonomous vehicles.
2. AV Value of Time factor: Scales how users perceive time spent in AVs.
3. AV Density factor: Scales the number of AVs that get generated, as a proxy for the space (per person) an AV takes up on the road.
4. Induced demand factor: Scales the overall trip generation rates.

Policy levers

1. Congestion pricing:
   - *policy_tarif*: Sets the pricing level.
   - *policy_tarif_time*: Determines when the pricing is active (e.g., peak hours, all day).

- *policy_area*: Defines the geographical area where the pricing is applied.

2. Speed reduction:
    - *policy_speed_reduction*: Probability of reducing speed on a given road.
    - *policy_area*: Defines the area where speed reductions are applied.

These scenario uncertainties and policies levers can be combined and varied into different scenarios and policies to explore their impacts on the transportation system. The scenarios and policies explored in this research are discussed in Appendix D.

7.9 Journey Management

The *Journey* class encapsulates all information about a single trip:

- It tracks the origin, destination, mode, costs, and timings of each trip.
- For car and AV trips, it interfaces with the UXsim traffic simulation to schedule vehicle movements.
- It handles the logic for trip chaining, ensuring that agents return to their original location and maintaining mode consistency (e.g., if an agent leaves with a car, they must return with a car).

7.10 Data Collection and Analysis

The model collects data at multiple levels:

- Agent level: Individual trip details, mode choices, and costs.
- Network level: Traffic conditions from UXsim (speed, density, flow) for each network link.
- System level: Aggregated metrics like mode shares, total vehicle kilometers traveled, and parking occupancy.

Data is collected at regular intervals and stored for post-simulation analysis. The *process_results* function in the *UrbanModel* class handles the aggregation and storage of this data.

Appendix B: Assumptions

This appendix lists the most important assumptions made in the model design and implementation.

Agent behavior

1. Rational decision-making: Agents make mode choices based on minimizing comfort-adjusted perceived costs, including monetary costs and time costs weighted by their value of time, and a comfort factor.
2. Perfect information: Agents have complete knowledge of travel times and costs for all available modes.
3. Heterogeneous value of time: Each agent's value of time is drawn from a lognormal distribution, representing varying sensitivities to travel time, and differs by mode (KiM 2023).
4. Trip generation: The number and timing of trips for each agent are determined probabilistically based on hourly trip probabilities derived from ODiN 2023.
5. Trip chaining: Agents always return to their origin location after each outbound trip, creating simple two-leg trip chains.
    - ODiN 2022 data showed 43.8% of trips start at home, 43.8% end at home (total 87.6%), and only 12.4% are neither.
6. Mode availability: An agent's available modes depend on car ownership, possession of a driver's license, and the previous leg of their trip chain.
    - Notably, if a car is used for the first leg of a trip, it must be used for the return leg as well.
7. Bicycle ownership: All agents are assumed to have access to a bicycle.
8. No en-route mode switching: Once a mode is chosen for a trip, it cannot be changed during the journey.
9. No trip cancellation: Agents do not cancel trips due to high costs or unavailable modes.
10. No carpooling or ride-sharing: Each car or AV trip represents a single agent.

Traffic model

1. Mesoscopic simulation: Traffic is modeled at a medium level of detail, balancing computational efficiency with realistic traffic dynamics.
2. Platoon-based representation: Vehicles are grouped into platoons (of 10 by default) for computational efficiency, with each agent representing multiple actual vehicles.
3. Dynamic User Equilibrium: Drivers choose routes based on experienced travel times, updating their choices periodically.
4. Simplified intersection behavior: Detailed intersection dynamics (e.g., traffic signals, turn lanes) are not explicitly modeled.
5. Constant road capacity: Road capacities do not change due to weather, incidents, or other temporary factors.
6. Homogeneous vehicle types: All vehicles are assumed to have the same physical characteristics and performance.
7. External traffic: Traffic entering and leaving the study area is modeled based on fixed origin-destination matrices and time-of-day factors.

Data

1. Population distribution: Agent locations are based on actual population data at the 4-digit postal code level, as reported by the CBS for 2020 (CBS-postcode).
    - In total 991.575 people live in the simulation area.
2. Car ownership and driver's licenses: Distribution of car ownership and driver's licenses is based on 4-digit postal code level data (CBS-mobility).
    - On average, 31.5% of agents in the simulation area own a car, and thus have car as a mode option. This varies per postal code area.
3. Road network: The road network is derived from OpenStreetMap data, on September 30, 2024, using OSMnx 2.0.0b2. It includes ternary roads and larger roads, with speed limits, lane counts and lengths.
    - The road network contains 1575 nodes and 3328 edges.
4. Travel times and distances: Non-car mode travel times and distances are based on Google Maps Distance Matrix API data (Google-Maps-API), on Thursday 2024-09-17 at 08:00 (a normal workday without major construction).
    - Note that cycling and public transit times are relatively stable throughout the day, while car travel times can vary significantly.
5. Trip generation rates: Hourly trip probabilities are derived from the Dutch National Travel Survey (ODiN 2023).
6. Origin-destination patterns: Origin-destination lookup is based on matrices from the V-MRDH transport model.
    - Only the total values for all modes are used, not the per-mode values, since mode-choice is integrated in the model.
7. Value of Time: Default values of time for different modes are based on Dutch transportation studies (KiM-valuation). AV is assumed to be the same as car (and varied in experiments with the AV VOT factor).
    - The default value of times are €10.42 for car, €10.39 for bike, and €7.12 for transit.
8. Default AV costs are based on own research, as no public data was available. A survey was put out on Reddit, on which a linear regression model was estimated (Waymo-pricing).
    - The default AV costs are €3.79 plus €1.41 per kilometer and €0.40 per minute.

Other

1. Static land use: The model assumes no changes in land use or population distribution during the simulation period.
2. No seasonal variations: The model does not account for seasonal changes in travel behavior or weather conditions.
3. No special events: The impact of large events (e.g., sports matches, festivals) on travel patterns is not considered.
4. Constant fuel/energy prices: The model assumes static prices for fuel and energy throughout the simulation.
5. No technological improvements: The model assumes constant vehicle efficiency and performance over time.
    - AV density and costs can be adjusted to represent technological improvements.
6. Simplified AV behavior: Autonomous vehicles are assumed to operate similarly to human-driven vehicles, with adjustments only to cost structure and value of time.

7. No adaptation of public transit: The public transit system is assumed to remain constant, not adapting to changes in demand or competing modes.

Appendix C: Limitations

Agent behavior

The Agent mode-choice model is the most limited part of the model, mainly because of data-availability and computational constraints. Ideally an activity-based model would be used, but this would require carefully designed surveys with large sample sizes, which weren't available.

Some specific limitations include: 1. Limited behavioral complexity: The model does not capture complex decision-making processes, psychological factors, or habitual behaviors that may influence mode choice. - Implementing more complex behavioral models needs carefully designed stated-preference (SP) studies, which also collects socio-economical data. Only revealed-preference studies were available, but different to fit to scenarios and modalities that currently do not exist. 2. Lack of sociodemographic factors: Beyond value of time, the model does not consider how factors like age, income, or household composition affect travel behavior. - Data for these factors is available, but would only make sense to use with proper stated-preference studies (or other calibrated models). 3. Simplified trip chaining: The model only implements simple two-leg trip chains, not capturing more complex trip patterns (e.g., home-work-shop-home). - More complex trip chaining would also require additional data on activity patterns. 4. No long-term adaptation: Agents do not learn or adapt their behavior over time based on experiences. - Implementing learning behaviors would require longer simulation periods, for which compute budgets where out of scope for this study. 5. Limited mode options: The model considers only four modes (car, bike, transit, AV), not including options like walking, e-bikes, or shared mobility services. - Adding more modes would require additional data and increase the complexity of the mode choice model. 6. Limited social considerations: The model does not account for social influence on mode choice or household-level decision making. - Social factors like peer effects and household car sharing could significantly impact AV adoption patterns. 7. No explicit parking behavior: While parking occupancy is tracked, parking availability and search time are not incorporated into mode choice decisions. - This could underestimate the full costs of car-based travel, especially in dense urban areas.

One interesting thing to note is that for most metrics, like congestion, it doesn't matter how the agents make their decisions, as long as they are consistent. The model is about the system-level effects of the decisions, rather than the individual decisions themselves. Of course the feedback loops and stabilizing mechanisms would be different for different decision-making models, leading to different system-level outcomes.

Highly recommended for future research is to conduct a stated-preference study, which can be used to calibrate the model to real-world data. Learning mechanisms and an activity-based model would also be beneficial to capture more realistic agent behavior.

Traffic Model

The traffic model mainly lacks in details on crossings and intersections, which are not specifically modeled. The remainder of the model is relatively detailed, but still has some limitations:

1. Limited network detail: The mesoscopic approach does not capture detailed vehicle interactions or traffic signal operations.
    - A more detailed microscopic simulation would be computationally intensive for a city-scale model.

2. Simplified parking model: Parking is modeled at an aggregate level, not considering specific parking locations or search time. Parking costs were also not included.
    - Detailed parking modeling would require extensive data on parking supply, which wasn't accurately available.
3. No consideration of freight traffic: The model focuses on passenger transport, not explicitly modeling freight movements.
    - Freight transport is a relatively small part of urban traffic, but could be included in future versions.
4. Limited representation of public transit: Transit is modeled simplistically, not capturing details of transit routes, schedules, or capacity constraints.
    - Detailed transit modeling would require integration with a separate transit simulation model.
    - Peak hour capacity constraints and crowding effects are not considered.
5. No modeling of active modes infrastructure: The model does not consider the impact of bicycle lanes or pedestrian infrastructure on mode choice and traffic flow.
    - Bicycle and public transport don't face many delays due to congestion, so the impact of infrastructure is limited.
    - It was found that bicycle travel times are remarkable consistent with distance for bicycle trips (see travel_time_distance_google.ipynb), so an explicit model was not deemed necessary as long as the lookup tables have enough detail.
6. Simplified intersection dynamics: The model uses default merge priorities and does not include traffic signal timing or turn lane specifications.
    - While adequate for system-level analysis, this may affect the accuracy of local congestion patterns.
7. Homogeneous vehicle characteristics: All vehicles within a mode are assumed to have identical performance characteristics.
    - In reality, different vehicle types (e.g., electric vs. conventional) could affect traffic flow and mode choice.

Data

Data availability is always a limitation in ABM models, and this model is no exception. Especially validation data for congestion, mode choice and AV pricing was hard to come by. Some specific limitations include:

1. Temporal specificity of travel time data: Google Maps API data used for non-car modes represents conditions at a specific time, not capturing variations throughout the day.
    - Collecting time-varying data for all origin-destination pairs would be prohibitively expensive (current lookups were 156.25 USD, within a 200 USD free tier).
2. Aggregation of origin-destination data: Trip distribution is based on larger traffic analysis zones used by V-MRDH, not capturing fine-grained variations in travel patterns.
    - More detailed O-D data was not available. A problem is that the more fine-grained the data, the more sparse it becomes, decreasing the signal-to-noise ratio.
3. Simplified representation of transit costs: The transit cost model uses a simplified distance-based approach, not capturing the complexity of real-world fare systems.

    - Implementing detailed fare structures for all transit operators would require extensive data collection, which was out of scope.
4. Limited validation data: The model lacks comprehensive data for validating results, especially for future scenarios involving autonomous vehicles.
    - Detailed validation data for emerging transportation technologies is inherently limited. Behavior was examined to see if it was plausible, but no real-world data was available to compare to.
5. Static infrastructure data: The road network and transit services are based on a single snapshot, not capturing planned changes or maintenance effects.
    - While major planned infrastructure (like the new A16) was included, smaller changes could affect local travel patterns.
6. Limited calibration data: While mode shares could be validated against ODiN data, detailed validation of traffic patterns was constrained by data availability.
    - Attempts to obtain commercial traffic data for validation were unsuccessful.

Other

The main other limitation is the lack of long-term dynamics and feedback loops. The model is a static scenario analysis, not capturing how the system might evolve over time. This was a conscious choice in the model scope, since this study was primarily about how the urban transportation system might respond to AV adoption and policy interventions, and how people might make different day-to-day decisions based on these changes.

Some specific limitations include: 1. Static scenario analysis: The model simulates a single day, not capturing longer-term evolving dynamics of AV adoption and system adaptation. - Long-term dynamic simulations would require additional assumptions about technology adoption and system changes, increasing uncertainty. 2. Limited policy options: While the model includes some policy levers (congestion pricing, speed reductions), it does not cover the full range of potential policy interventions. - Implementing a wider range of policies was consciously avoided, since this study was primarily about the system-level effects of AVs. 3. No feedback between transportation and land use: The model does not capture how changes in the transportation system might influence land use patterns over time. - Land use requires long-term simulations and detailed urban planning models, which were out of scope. 4. Limited environmental impact assessment: The model does not directly calculate emissions or other environmental impacts of transportation choices. - Adding detailed environmental impact modeling would require additional data on vehicle characteristics and emissions factors. However, the distance traveled by car and AV is available, which is a good proxy for emissions. 5. No consideration of equity impacts: The model does not explicitly address how changes in the transportation system affect different socioeconomic groups. - Equity analysis would require more detailed sociodemographic data and additional post-processing of model outputs. 6. Simplified AV implementation: The model treats AVs essentially as cheaper, more comfortable cars, not capturing potential transformative impacts on urban form or travel behavior. - The exact impacts of AVs are still uncertain, and more complex representations would require speculative assumptions. - Density is used as a proxy for the space an AV takes up on the road and the average number of people in a car. This is a simplification, but a good first-order approximation. 7. Limited geographic scope: The model focuses on the Rotterdam area, potentially missing broader regional or national-level impacts. - Expanding the geographic scope would require significantly more data and computational resources. Other regions could be relatively easily added, population and network data is available for the whole of the Netherlands. OD-matrix data would need to be added if going beyond the MRDH area. 8. Weather and seasonal effects: The model does not account for how weather conditions or seasonal patterns affect mode choice and traffic flow. - This could be particularly relevant for cycling behavior and AV operations. 9. Time-of-day variations: While trip generation varies by hour, mode characteristics (like transit frequencies) are static throughout the day. - This simplification could affect the accuracy of off-peak travel patterns, especially for transit in weekends, evenings, and nights.

Appendix D: Experimental setup

This appendix describes the experimental setup used in this study. Two main experiments were conducted: a scenario analysis exploring uncertainties in autonomous vehicle (AV) adoption and a policy analysis testing various interventions across different scenarios.

1. Scenario Analysis

The scenario analysis employed a full-factorial design to explore four key uncertainties related to the adoption and impact of autonomous vehicles. These uncertainties were represented by the following variables:

1. AV Cost Factor (*av_cost_factor*): Represents the relative cost of using AVs compared to the current cost AVs (as operated by Waymo in Los Angeles in September 2024 (Waymo-pricing), see Appendix B for more details).
2. AV Value of Time Factor (*av_vot_factor*): Reflects how users perceive time spent in AVs compared to conventional vehicles.
3. AV Density (*av_density*): Represents the space efficiency of AVs on the road compared to conventional vehicles.
4. Induced Demand (*induced_demand*): Reflects the potential increase in overall travel demand (either due to the introduction of AVs or other mobility or macroeconomic factors).

Note that AV density represents the average space a single person transported with an AV takes up on the road (a lower value means more people can be transported with the same road space). How that density is achieved is not relevant for the simulation outcomes, but it can be for interpretation. AV density can be improved by either increasing the average number of people in a car (picking up more people on the way, driving less empty between trips) or taking up less road space (smaller vehicle sizes, faster reaction times, platooning). The table below shows the values used for each variable in the full-factorial design:

Variable	Values
av_cost_factor	1.0, 0.5, 0.25, 0.125
av_vot_factor	1.0, 0.5, 0.25
av_density	1.5, 1.0, 0.5, 0.333333
induced_demand	1.0, 1.25, 1.5

This design resulted in a total of 4 × 3 × 4 × 3 = 144 unique combinations, each representing a possible future scenario for AV adoption and its impacts.

The scenario analysis was executed using the *run_model.py* script, which implemented the full-factorial design and managed the parallel execution of simulations for each combination of variables.

Other relevant model settings for the scenario analysis included:

- Time step: 5 minutes (1/12 hour)
- Simulation period: 5:00 to 24:00 (19 hours)
- Choice model: Rational value of time
- AVs enabled: Yes
- External vehicle load: 0.8

- UXsim platoon size: 10
- Car comfort factor: 0.5
- Bike comfort factor: 1.33

2. Policy Analysis

The policy analysis was designed to test the effectiveness of various policy interventions across different AV adoption scenarios. This analysis used a set of predefined scenarios and policies, as specified in the *scenarios_policies.py* file.

2.1 Scenarios

Eight scenarios were defined, representing different possible futures for AV adoption and its impacts. Table A.2 summarizes these scenarios:

Scenario Key	Description	*av_cost_factor*	*av_density*	*induced_demand*
0_current	Current situation	1.0	1.5	1.0
1_moderate_progress	Moderate AV progress	0.5	1.0	1.125
2_extensive_progress	Extensive AV progress	0.25	0.5	1.25
3_extreme_progress	Extreme AV progress	0.125	0.333333	1.5
4_private_race_to_the_bottom	Cheap, inefficient AVs	0.125	1.5	1.25
5_mixed_race_to_the_bottom	Cheap AVs, mixed efficiency	0.125	1.0	1.25
6_shared_race_to_the_bottom	Cheap, efficient AVs	0.125	0.5	1.25
7_dense_progress	Efficient AVs, moderate demand	0.25	0.333333	1.125

All scenarios used an *av_vot_factor* of 0.5.

2.2 Policies

Nine different policy combinations were tested, varying in their approach to speed reduction, congestion pricing, and geographical scope. Table A.3 summarizes these policies:

Policy Key	Area	Speed Reduction	Tariff	Tariff Time
0_no_policy	City	0	0	Day

Policy Key	Area	Speed Reduction	Tariff	Tariff Time
1_autoluw_peak	Autoluw	1	5	Peak
2_autoluw_day	Autoluw	1	5	Day
3_city_peak	City	1	5	Peak
4_city_day	City	1	5	Day
5_city_speed_reduction	City	1	0	Day
6_city_peak_tarif	City	0	5	Peak
7_city_day_tarif	City	0	5	Day
8_all_out	City	1	10	Day

Where: - "Autoluw" refers to a specific low-traffic area within the city (Rotterdam-verkeerscirculatieplan), and city indicates the entire city area (all roads in the main network). - Speed Reduction: The fraction of roads in that area that get a 20 km/h maximum speed reduction (0 meaning 0% of roads, 1 meaning 100% of roads) - Tariff: Congestion charge in euros per trip, if either the origin or destination is in the area - Tariff Time: "Peak" = applied during peak hours (7:00-9:00 and 16:00-18:00), "Day" = applied throughout the day (6:00-19:00)

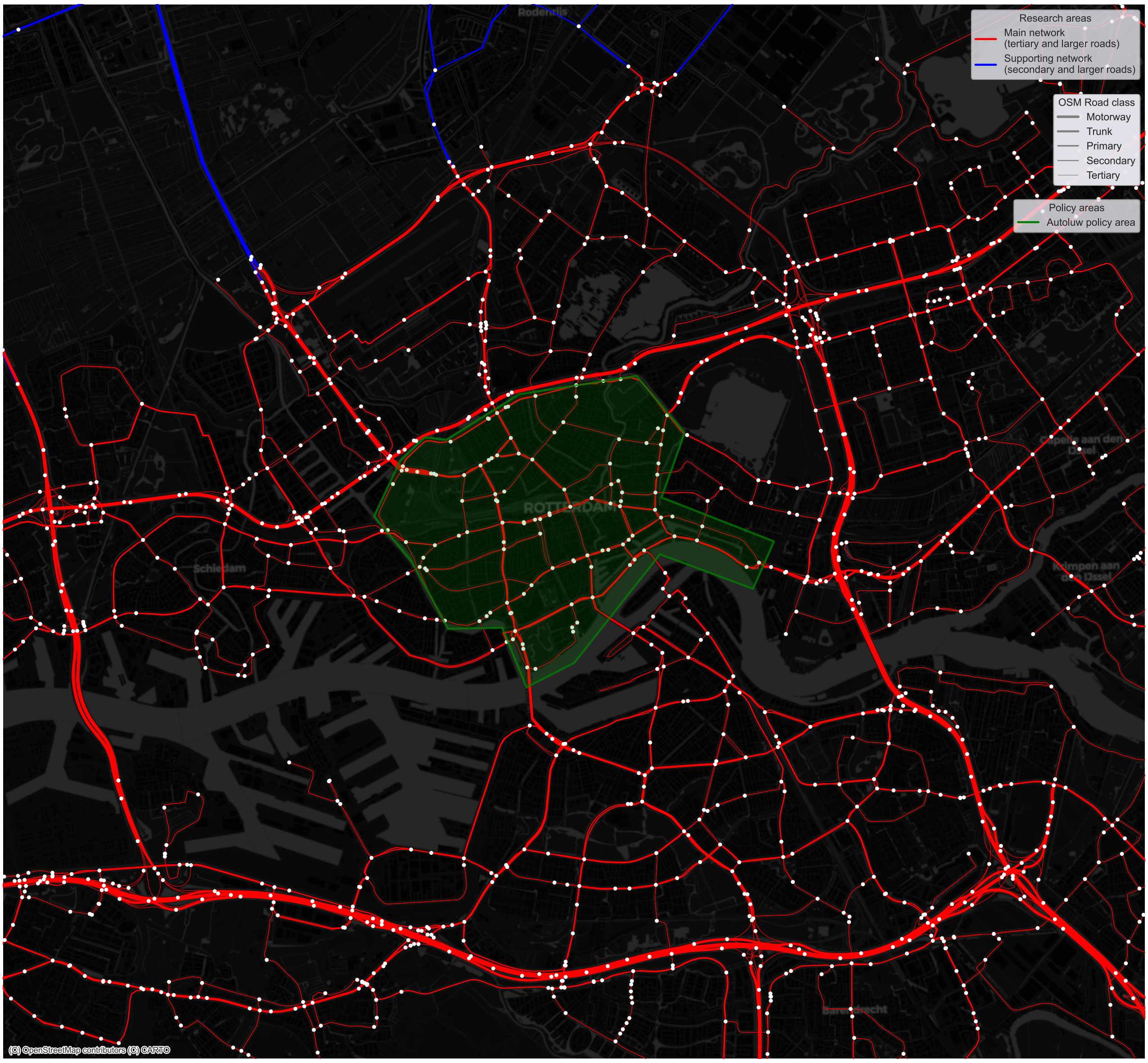

Fig D.1: The network with the autoluw area highlighted in green.

The following PC4 areas are within the autoluw area (and thus potentially affected by the policies):

- Rotterdam Centrum (1): [3011, 3016, 3015, 3012, 3014, 3013]
- Delfshaven (2): [3022, 3021, 3023]
- Noord (3): [3039, 3041, 3037, 3032, 3038, 3036, 3035, 3033]
- Kralingen (4): [3031]

AV pricing, if enabled for the autoluw area, will affect about 13% of the agents in the simulation. 130.835 of 991.575 inhabitants live in the autoluw area, of which: - Rotterdam Centrum (1): 38.705 - Delfshaven (2): 31.410 - Noord (3): 52.420 - Kralingen (4): 8.300

The city area covers the all 125 PC4 areas in the research area and thus all agents.

2.3 Experimental Design

The policy analysis involved running simulations for all combinations of the 8 scenarios and 9 policies, resulting in 72 unique experiments. This was implemented in the `run_model_2.py` script, which managed the execution of simulations for each scenario-policy combination.

For each combination, the script: 1. Combined the scenario and policy parameters 2. Generated a unique suffix for the output files 3. Checked if the simulation had already been run (to avoid duplication) 4. Executed the simulation if needed

The simulations were run in parallel across multiple cores to improve computational efficiency.

3. Data Collection and Analysis

For both the scenario and policy analyses, each simulation run collected the following data:

1. Journey details: Origin, destination, mode, travel time, costs, etc.
2. Traffic conditions: Speed, density, and flow for each network link
3. Parking occupancy over time

This data was saved in various formats (Feather files for journey data, Python pickle files for UXsim and parking data) for subsequent analysis.

The collected data allowed for the evaluation of various metrics, including: - Mode share distributions - Network performance (average speeds, congestion levels) - Parking demand patterns - Total vehicle kilometers traveled - Distribution of travel times and costs

These metrics were used to assess the impacts of different AV adoption scenarios and the effectiveness of various policy interventions.