# Agent-based car sharing

*Investigating the effects of car sharing and parking policies on travel behaviour in Enka Ede using Agent-based modelling.*

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https://github.com/EwoutH/SEN9120-ABC

## Summary

This study explores the use an Agent-Based Model (ABM) to understand travel behaviours and social dynamics in the ENKA neighbourhood of Ede, the Netherlands. The focus is on identifying the most important factors that influence modality choice behaviour and explaining emergent travel behaviour under different circumstances. To achieve this, an ABM was created to examine the effects of transitional policies on modality choice behaviour, vehicle ownership, and resistance in ENKA.

The model simulates three types of agent behaviour, including modality choice, social influence diffusion, and vehicle or subscription acquisition. Private car ownership dominates ENKA due to the high availability of parking spaces and a lack of shared mobility options. To shift travel behaviour from car ownership and use to sustainable travel modes, the model experiments with the removal of parking spaces, an increase of shared cars, and parking fees.

The experiments test three different policy interventions using a design that includes five experiments, resulting in 11 experiment runs. We found that removing parking spots was essential to reduce the car count in the neighbourhood. We also concluded that when people sell their car, trips previously taken by car are not exclusively replaced by the shared car, but distributed among shared cars, bikes and public transport. Introducing paid parking has no significant effects as a standalone policy, but can help soften the resistance from removing parking spots. A combination of the three policies proposed had the most coherent effect on all KPIs, and leads to a shift towards public transport, bicycles, and shared cars.

The paper recommends future research to add more external factors to make the effect of continuous interactions between residents more observable. Additional research and or surveys into consumer preferences are also crucial for correct initialisation of independent variables, mainly the modality preferences. The interaction effects of these variables and the policy interventions should be analysed. Despite the limitations, the model provided meaningful and actionable insights.

Overall, this study demonstrates the importance of simulating the heterogeneity of agent behaviour accurately to capture the complexity of the real world. The results suggest that ABMs can be a useful tool for policymakers and researchers to better understand travel behaviour and the consequences of policy interventions that can lead to sustainable travel choices.

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# 1. Introduction

Consumer behaviour largely determines the impact of choices in the energy transition and the transition to a circular economy. An important part of the transition towards a climate-neutral and circular society is determined by people's mobility mode choices. Consumers influence each other's choices regarding short-term decisions such as daily travel modality choices and long-term decisions such as buying a vehicle or subscription. E.g. If a neighbour has a pleasant experience with the train, one might be more inclined to choose this modality too or buy a rail discount subscription. Furthermore, the behaviour of other stakeholders is important. A municipality can introduce a parking policy and companies can offer car-sharing. Finally, the structure of the system is important: if a neighbourhood is close to a train station, residents can more easily be encouraged to take the train. Similarly, the availability of parking spaces may influence the level of car ownership in a neighbourhood.

To realise a future with more sustainable travel behaviour, it is necessary to combine relevant knowledge from practice, behaviour studies, and natural scientific knowledge about the effects of transitional policies. A model is a simplified representation of reality that can help bring these factors together to better understand reality, explore possible futures, and support decision-making. Agent Based Models (ABMs) specifically are dynamic models that build up the dynamics of systems from the bottom up and can therefore show how social practices can grow from individual behaviour to the behaviour of the majority (Jager, 2021). This phenomenon is called 'emergence'. Emergence refers to complex behaviours or patterns emerging from the interactions of underlying components (Holland, 2000). When the aggregate behaviour of a system is not predictable from the behaviour of individual agents, ABMs are a useful tool. In ABM, agents can interact with each other and their environment, which can result in novel patterns that can be observed at a macro level (Bonabeau, 2002). Thusly, by building, exploring and using ABM, consequences of choice behaviour and social dynamics can be explored for different agents involved in a system.

This paper describes an ABM that was created for the National Institute for Public Health and the Environment (RIVM). The RIVM is currently experimenting with the application of ABMs in cases of transitional policies that stimulate sustainability and circular economy to gain insight into the consequences of interventions. In the case of this model, the focus is on the neighbourhood level to examine how different interventions can contribute to a sustainable living environment and the energy transition simultaneously. The selected neighbourhood for this model is ENKA in the municipality of Ede. The model is used to identify what stakeholders' behaviours are important for successfully implementing transitional policies in the ENKA neighbourhood. The transitional policies that will be researched in the model are removing parking spaces, increasing shared cars, and introducing parking costs. These policies are all meant to discourage using and purchasing private fossil fuel-driven cars and stimulate shared mobility and public transport.

Although the decrease in fuel-based car use has clear benefits for the environment, climate, health, and circular economy, people tend to have an emotional attachment to their cars (Ikezoe et al., 2020). Therefore, implementing policies that discourage car ownership is expected to cause resistance among ENKA neighbourhood residents. Furthermore, residents are subject to many factors such as interactions, personal preferences, random chance, vehicle availability and many more in their choice behaviour. By creating and experimenting with an ABM for ENKA Ede, this paper aims to identify the most relevant factors for modality choice behaviour. Besides, the model aims to exhibit and explain the emergent travel behaviour in ENKA Ede under different circumstances. Accordingly, the pitfalls of implementing these and possibly similar transitional policies can be pinpointed.

The research question that is specified in this case and is answered by this paper however is:

> *'What is the emergent effect of implementing transitional parking and car sharing policies that discourage private car ownership and use, on modality choice behaviour, vehicle ownership, and resistance in ENKA Ede?'*

After this introduction, first the conceptualisation will be discussed, in which the problem is identified, a system decomposition is created, and the behavioural model is discussed. The model will be formalised by defining its variables, statistical distributions and equations. The implementation and verification of the model are reported, after which the experimental design and results are presented, as well as the sensitivity analysis. Thereafter, certain aspects of the model are validated. Finally, the model limitations, concluding remarks, and the future research suggestions are discussed.

# 2. Conceptualisation

## Problem identification

The neighbourhood ENKA Ede is a new housing estate located next to the 'Ede-Wageningen' station which makes it very reachable with public transport. There is one primary school in the neighbourhood, but no other schools. There are also no shopping facilities in the neighbourhood, nor will they ever as these are not included in the spatial plan of the neighbourhood. Although there is a station nearby, a dominance of private car ownership is observed in ENKA Ede. This is partly due to the wide availability of parking places. ENKA Ede has a parking norm of 1.7 cars per household, which is very high. Furthermore, there are not many modes of shared mobility available in the neighbourhood. Resultingly, the current emergent pattern in the neighbourhood is intensive car use versus little use of shared mobility and public transport, congested traffic during rush hours, unsafe streets for children around schools, heavy climate impact, and a lack of greenery in the neighbourhood.

The desired emergent pattern is a modality choice shift from private cars to shared mobility, public transport, and other emission-friendly modes of transportation. This modality shift is expected to solve the road congestion and safety problems in addition to making ENKA Ede a more sustainable neighbourhood. To accomplish this shift in modality choice, the municipality of Ede wants to experiment with different transitional policies concerning parking places and costs. Additionally, the municipality of Ede aims to collaborate with the Hely mobility hub. This is a start-up that offers various modes of sharing mobility located in the ENKA neighbourhood. The municipality wants to reward residents of the neighbourhood that get rid of their private cars and subscribe to Hely's sharing mobility services. However, the RIVM held multiple stakeholder meetings to gain insight into the perspectives of residents and other stakeholders on the sustainable transition of mobility in their neighbourhood. The following barriers to using alternatives and problems with interventions became evident:

- Household families and friends live outside of ENKA Ede and are not always reachable with public transport.
- People in the neighbourhood that are less physically able need their car in front of their house.
- There are multiple worries about shared cars concerning their inconsistent availability of them, ease of use, added travel time, steep costs, and child seats for the car.
- It is economical for residents to drive their car until it is deprecated.
- The neighbourhood has been built this way, converting parking spaces is a big operation.
- There is no grasp on the presence or magnitude of neither support nor resistance towards the sustainable modality choice shift. Resistance is expected because driving is a habitual behaviour that is difficult to break, owning a car can be a status symbol, cars are deemed to be the easier mode of transport, many people already own a car, so no added costs and people deem cars to be essential.

To eventually overcome these barriers, data is needed on the resistance against or support for the sustainable mobility transition. Therefore, an ABM is built to gain insight into the consequences of the different interventions in ENKA Ede. By experimenting with the model, the behaviour that emerges in the system of ENKA Ede after the interventions can be understood. Thus, the municipality of Ede can use the model outcomes to evaluate different policy choices in the neighbourhood. To create the model, it is important to make a decomposition of the system that is ENKA Ede. This decomposition aims to further describe the ENKA neighbourhood, its different components, and the system boundaries. Here we aim to answer the question: *'Who does what with whom, how, when and where?'*. Firstly, the structure of the system will be delineated by identifying the relevant concepts, agents, objects, states, properties, and interactions to the model.

## System decomposition

To create an overview of the different agents, objects, and interactions that are relevant to this ABM, a mind map was created using Freeplane. This mind map shows the different agents and objects involved in the system as well as their behaviours, properties, functions, and possible states. Furthermore, it describes the environment that the agents and objects interact in and with for this model. Thereafter, the most relevant interactions between agents, agents and objects, and agents and the environment are described. The mind map is shown in Figure 2-1, and in Appendix A for higher resolution.

### Agents

Agents in ABM are described as individual entities that can interact with each other and their environment. Agents have their own set of properties, states, behaviours, and decision-making processes. Because agent behaviours and decision-making processes drive the emergent behaviour of systems, agents are a crucial part of ABM (Gilbert & Troitzsch, 2005). Another characteristic of agents is that they are adaptive. This means that the behaviour of agents can change over time in response to changes in their environment or interactions with other agents and objects (Heckbert et al., 2010). In the case of this model, the adaptivity of agents first allows us to observe different emergent patterns when variables in the environment are altered. Thereafter, the change in behaviour that occurs due to the interactions between agents can be analysed over time. The only agents in the model that is built are the residents that live in ENKA Ede.

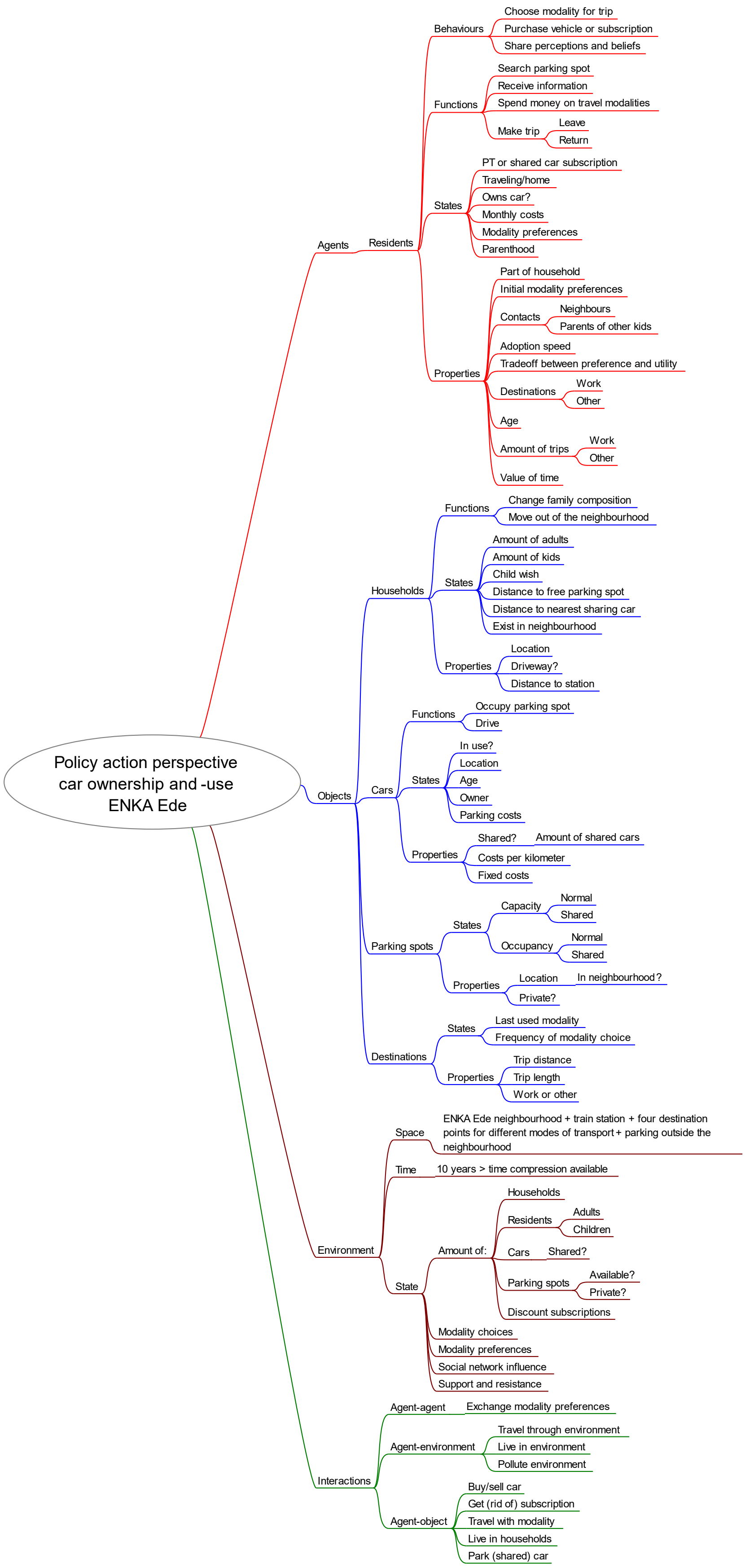


*Figure 2-1: Mind map of system decomposition.*

## Objects

Objects in ABM are non-decision-making entities that exist in the systems environment but do not have any behavioural rules. Objects cannot interact with other objects or agents, but they can be interacted with. E.g. can be owned or used by agents. Objects do have properties, states, and functions just like agents. The conceptual functions of agents and objects in this model (see Figure 1) are processes that entities go through due to model manipulations and interactions that cause the entity states to change. No decision-making is involved in these processes.

There are four objects in this model: households, cars, parking spots, and destinations. Firstly, residents live in households, so households determine the location of residents and therewith their neighbours. Furthermore, individual residents can be born into households or children can move out from the age of 18. Whole families can also move into or out of the households in the system. Private cars are both owned and used by residents whereas shared cars can only be used by the residents, they are not owned. Additionally, private cars can be sold and bought by residents. Cars can occupy parking spots when they are parked by residents. The capacity of parking spots constantly changes with residents leaving from returning to the neighbourhood in cars. Finally, the residents all have a set of destinations that they travel to and back from for work or other purposes.

## Environment

The environment of a system in ABM refers to the physical context in which agents exist and interact with each other and the system around them. The environment includes both static and dynamic factors that influence agent behaviour. The environment of ABMs can be manipulated to simulate the effects of interventions and policies. The environment of a system can be defined by its spatial and temporal dimensions as well as its states (Bonabeau, 2002). The spatial dimension defines the physical layout of a system and the temporal dimension determines how the environment of the system changes over time. The spatial dimension of this model is bounded by the edges of the ENKA Ede neighbourhood. Furthermore, the processes of this model occur on three different time scales. There are daily, monthly, and yearly processes. To increase the speed of the model, time compression is possible. This means that the number of days in months or months in years can be decreased without affecting the model functionality. The ticks of the model are in monthly resolution because this is the level at which data is most relevant to observe.

## KPIs

Finally, it’s important to define what metrics would indicate if the measured policies have an effect and if that effect is desired. Therefore, eight key-performance indicators are selected that will quantify the effect of the policy interventions.

The number of trips for each modality are the first four KPIs. They give an indication how resident mode choice changes under different policies and scenarios. The number of cars and number of subscriptions of both public transport and shared cars are also measured. Finally, the average preference for cars are measured, since the model penalizes parking outside of the neighbourhood as a (negative) external benefit.

All KPIs are measured over time to give insight in dynamic behaviour and system robustness, resilience, and stability.

## Conceptual behaviour model

Through interaction, the individual behaviour of agents can lead to emergent phenomena. Therewith the agent behaviour largely affects the dynamics and outcomes of the system that is modelled. To capture the complexity of the real world, it is important to simulate the heterogeneity of agent behaviour as accurately as possible (O'Sullivan et al., 2012). From the system decomposition (Figure 2-1), it becomes clear that three types of agent behaviour will influence the model dynamics of this system: modality choice for making a trip, the diffusion of perceptions and beliefs, and the acquisition vehicles or subscriptions. The following subsection will describe how these behaviours will be simulated in the model of ENKA Ede and how the different behaviours are interconnected. Figure 2-2 shows how the different behaviours are conceptually combined into one model.

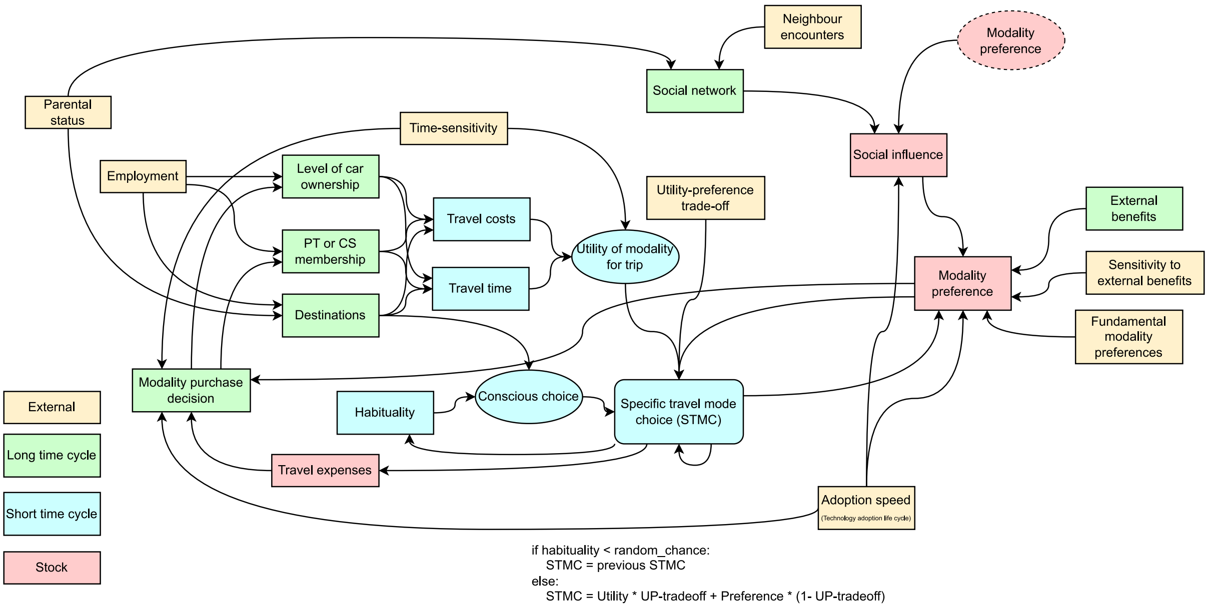


*Figure 2-2: Flow diagram of the conceptual agent behaviour model.*

The most important decision-making process that is to be simulated in this model is the travel mode that residents choose for the trip that they are about to make. This report's decision-making model elements are derived and combined from existing travel mode choice behaviour models (Klöckner & Blöbaum, 2010; Vij et al., 2013). The modality choice is determined by the resident's individual modality preferences and the utility of the modality for the trip if the resident makes a conscious choice. If the resident does not choose consciously, the resident chooses the last used modality out of habitual behaviour. When a conscious choice is made, the resident weighs their modality preferences against the utility of these all the modalities for the trip ahead. This choice depends on the trade-off between how much value a resident attaches to their personal preferences or subjective convenience.

### Personal modality preferences

A resident's personal modality preferences are established by foundational beliefs that are determined by the resident's character, the benefits and disadvantages of using different modalities, and the influence of their social network. The influence external benefits and disadvantages have on the modality preferences depends on how much a resident cares about these consequences. This might differ for different consequences. Furthermore, the social influence on a resident's modality preferences consists of the modality preferences conveyed by the people in this person's social network. The implementation of modality preference diffusion draws inspiration from a travel attitude change model by van Wee and Kroesen (2022) A resident's social network includes neighbouring contacts that are determined by the location of their household. If a resident has a child that goes to school, other parents with a child of the same age can also be part of a resident's network. The effect of social influence from contacts on a resident's modality preferences depends on the adoption speed of this person. The higher a person's adoption speed, the more impressionable they are. This is based on the diffusion of innovation in complex adaptive systems theory by Rogers et al. (2005).

### Utility of modality for trip

The adoption speed of a resident also influences how likely they are to purchase a vehicle or discount subscription for shared modalities, due to differences in travel expenses. The higher the adoption speed, the sooner a resident makes a modality purchase decision, if it can lower travel expenses. The travel expenses of a resident are the sum of costs from trips made with previous travel mode choices. Furthermore, the modality purchase decisions of a resident depend on how sensitive this resident is to potential travel time that is saved with a newly purchased vehicle or subscription. Lastly, a resident's modality preferences are a factor in their purchasing decisions.

By purchasing or selling a vehicle or subscription, the modality purchase decisions of residents establish whether they own a car or subscription. The employment of a resident can also affect the level of car and subscription ownership. E.g. lease cars, company fuel cards, and public transport business memberships. Employment also affects the list of destinations that residents have to travel to as they travel back and forth to work. Besides, this list is influenced by parenthood, if residents have young kids they have to drop off and pick up their kids at school. Together, the level of car ownership, subscription ownership, and destinations determine the travel costs and time of each trip. Logically, a trip's costs and travel time depend on the distance that someone has to travel. Public transport and shared car subscriptions can decrease the costs of the trip for these modes of transport. Furthermore, car ownership determines if a car is among the available options to compare on utility. Eventually, the travel mode with the lowest travel costs and -time has the highest utility for the trip. Time has a bigger influence on the utility when people are more time sensitive and Therefore, attach more value to time.

# 3. Model formalization

The following section will focus on the specification of the model by delineating the most important variables of the environment, agents, and objects. Additionally, it will elaborate upon the most important distributions and algorithms that have been implemented in the model to formalise the core functionalities of the model.

## Variables

Table 10-1 in Appendix C provides an overview of the different variables of the model. These variables represent the states and properties of the environment, agents, and objects in the model. Variables that required elucidation are shortly described in the table. As these variables cannot be manipulated in the interface of the model, they can be seen as independent variables.

The following table (Table 2) shows the variables of the model that can be changed with sliders in the interface of the model. The first three variables are the policy levers that will be experimented with in the model analysis. The other variables are all dependent as well as they can be changed but will not be manipulated. The initialised values of these variables are either supported by literature or by assumptions, both can be found in Appendix C. Although the dependent variables are not manipulated, they can be used for the sensitivity analysis, this will be explained in the sensitivity design section.

*Table 3-1. Slider variables with their ranges and initialised values.*

| | **Slider variables** | **Range** | **Model values** |
|---|---|---|---|
| *Policy levers* | parking-permit-costs | 0-200 | Varying |
| | amount-of-shared-cars | 0-168 | Varying |
| | remove-spots-percentage | 0-100 | Varying |
| *Dependant variables* | only-park-designated-spots | Boolean | On |
| | average-neighbour-contacts | 0-25 | 4 |
| | average-parent-contacts-per-child | 0-10 | 10 |
| | average-daily-neighbour-contacts | 0-5 | 0.5 |
| | average-daily-parent-contacts | 0-5 | 0.8 |
| | subscription-monthly-buy-sell-chance | 0-100 | 25% |
| | chance-of-household-moving | 0-25 | 10% |
| | chance-of-moving-out | 5-25 | 15% |
| | days-in-month | 2-31 | 31 |
| | months-in-year | 2-12 | 12 |
| | shared-car-costs-per-km | 0.05-0.8 | € 0.30 |
| | shared-car-costs-per-hour | 1-10 | € 3.25 |
| | car-costs-per-km | 0-0.3 | € 0.23 |
| | fixed-car-costs | 0-500 | € 257.00 |
| | public-transport-fixed-costs | 0-3 | € 1.08 |
| | public-transport-costs-per-km | 0-0.5 | € 0.20 |
| | work-trip-length | 1-12 | 8 hours |
| | other-trip-length | 0.5-6 | 2.5 hours |

| | | | |
|---|---|---|---|
| | mean-car-speed | 0-100 | 46.3 km/h |
| | mean-public-transport-speed | 0-100 | 34.8 km/h |
| | mean-bike-speed | 0-45 | 11.8 km/h |
| | social-adoption-multiplier | 0-1 | 0.1 |
| | initial-car-chance-parent | 0-100 | 65% |
| | initial-car-chance-child | 0-100 | 20% |
| | initial-public-transport-subscriptions | 0-100 | 25% |
| | initial-shared-car-subscriptions | 0-100 | 2% |
| | preference-penalty-parking-outside-neighbourhood | 0-10 | 0.5% |
| *Gamma distributions* | mean-distance-work | 0-100 | 44 km |
| | variance-distance-work | 0-800 | 440 |
| | mean-distance-other | 0-100 | 22 km |
| | variance-distance-other | 0-400 | 220 |
| | mean-value-of-time | 0-20 | 8.75 €/hour |
| | variance-value-of-time | 0-60 | 12 |
| *Poisson distributions* | mean-weekly-work-trips | 2-6 | 4.3 |
| | mean-weekly-other-trips | 0-10 | 6.8 |
| *Normal distributions* | initial-car-preference | 0-1 | 0.7 |
| | initial-shared-car-preference | 0-1 | 0.5 |
| | initial-bike-preference | 0-1 | 0.5 |
| | initial-public-transport-preference | 0-1 | 0.3 |

### Distributions

At the bottom of Table 2, some dependent variables in sliders are used for different distributions in the model. Some of the distributions in the model are fixed in the model, some have adjustable means, and some have adjustable means and variances. Firstly, the adoption-speed value that determines how impressionable residents are, is distributed over the residents with a normal distribution. This distribution is fixed with a mean of 0.5 and variance of 0.15 because these values best represent the diffusion of innovations curve by (Rogers et al., 2005). Figure 3 illustrates what this normal distribution looks like. Here the innovators, early adopters and laggards are assumed to be less impressionable than the early and late majority.

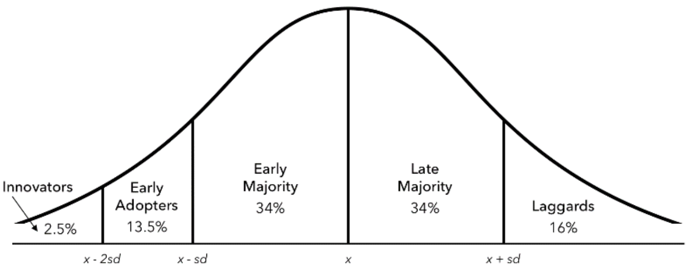


*Figure 3-1. Diffusion of innovations curve.*

*From Diffusion of Innovations (5th edition), by Rogers, E. M. (2003).*

The four different initial modality preferences are also distributed over the residents with a normal distribution. All four distributions have a fixed variance of 0.15 but their means are adjustable with sliders. Furthermore, the number of weekly work and other trips are allocated to the residents with a

Poisson distribution because discrete numbers were required for this value, the means of these distributions can be changed in sliders. Lastly, the distances of work and other destinations as well as the value of time residents are determined with Gamma distributions. Both the means and variances of these distributions can be altered with sliders in the interface of the model.

# Formulas

While agent decision making can be highly complex, especially with humans, it has to be formalised to be used in a model. Therefore, formula's were constructed for updating each environment variable, agent variables, and agent decisions. These are presented in Table 3-2.

*Table 3-2. Functional algorithms of the model.*

| | Formulas | Elaboration |
|---|---|---|
| *Initialise* | Effective car costs | For each destination, a resident has, effective costs including the value they attach to time are calculated for each mode of transport available to a resident. |
| | trip-distance * car-costs-per-km + (trip-distance / mean-car-speed) * value-of-time | |
| | Effective bike costs | Cycling is assumed to be free so the costs only depend on the travel time for each destination and a resident's value of time. |
| | trip-distance / mean-bike-speed * value-of-time | |
| | Effective public transport costs | The travel time for public transport to a destination also includes the bike ride between a resident's household and the station for a return trip. |
| | trip-distance * public-transport-costs-per-km + (trip-distance / mean-public-transport-speed + 2 * distance-station-from-household / mean-bike-speed) * value-of-time | |
| | Effective shared car costs | Shared cars typically have costs per kilometre and hour. The travel time is the same as with a normal car |
| | trip-distance * shared-car-costs-per-km + trip-length * shared-car-costs-per-hour + (trip-distance / mean-car-speed) * value-of-time | |
| *Daily* | Modality choice | If a new modality choice is made, firstly the utility of each mode of transport for a destination is established using min-max normalisation. The utility of each modality is multiplied by the resident's preference utility trade-off value. Then, the accompanying personal modality preference values for the modalities are multiplied by one minus the preference utility trade-off value and the two remaining values are added together. The modality that has the highest final value will be chosen as the new travel mode by the resident. |
| | utility-of-modality * preference-utility-tradeoff + modality-preference * (1 - preference-utility-tradeoff) | |
| | Car preference penalty | When a resident has to park their car outside of the neighbourhood due to a lack of capacity in parking spots, their car preference in their modality preference table is decreased with a small penalty. |
| | modality-preference-car * (1 – preference-penalty-parking-outside-neighbourhood * 0.01) | |

| | | |
|---|---|---|
| *Monthly* | Chance to sell car | If a resident owns a car and the total costs per month of non-car options are smaller than the total costs of a car, there is a chance a resident will sell their car. The difference in costs is divided by the total car costs to calculate what can relatively be saved, this is then multiplied by the preference utility trade-off. Thereafter, the difference between the average preferences of non-car options and the car preference is multiplied by the preference utility trade-off and added. This can decrease the chance of selling the car when the resident's car preference is bigger than the other modality preferences. |
| | (total-car-costs - total-costs) / total-car-costs * preference-utility-tradeoff + (preferences-without-car - modality-preference-car) * (1 - preference-utility-tradeoff) | |
| | Chance to buy a car | This function works the same as the sell car chance but is reversed as it determines the chance of buying a car when a resident does not own a car and the total monthly costs of a car are smaller than the costs of the other options. |
| | (total-costs - total-car-costs) / total-costs * preference-utility-tradeoff + (modality-preference-car - preferences-without-car) * (1 - preference-utility-tradeoff) | |
| | Update preference social network | The modality preferences of residents are updated daily and can change due to external benefits or penalties. Every month, these updated preferences are exchanged amongst residents and affect each other's modality preferences. Residents with a higher adoption speed value are more susceptible to these social influences. To nerf the effect of social networks, the adoption speed is first multiplied by the social adoption multiplier to get the 'alpha' value. A resident's modality preferences are multiplied by one minus alpha, and then the modality preferences of contacts are added after being multiplied by alpha. The higher the alpha value is for a resident, the more their modality preferences change with their contact preferences. |
| | modality-preference * (1 - alpha) + contact-preference * alpha | |

# 4. Software implementation

Based on the conceptualisation and formalisation above the model is implemented in NetLogo (Wilensky, n.d.). Version 6.3.0 is used, including the random, gis, table, and stats extensions.

NetLogo was chosen over other frameworks mainly due to its maturity and great ecosystem. NetLogo is a stable and stand-alone ABM package with great documentation including examples and extensions for most wanted abilities. It also contains good debugging and validation abilities, including the ability to watch (follow) agents and inspect their properties over time.

The biggest encountered limitation was keeping track of data within agents. The table extension helped, but it is more cumbersome than using dictionaries in Python for example. The second problem is that objects do not exist in NetLogo (it is not an object-oriented programming language). Another limitation is that running many experiments and gathering data with NetLogo can be more complicated and less scalable than with Python-based ABM packages. PyNetLogo is used (Jaxa-Rozen & Kwakkel, 2018) to solve this issue, and wrote Python scripts to initialize and run experiments and collect data from them.

The data analysis was done using Python 3.11, the data was saved using pickles, processed using Pandas 1.5 and plotted with Seaborn 1.12.

## Model structure

The model is structured in three parts:

- ABC_model.netlogo:
  - Interface with visualisation, sliders and metrics.
  - High-level functions: setup, go, and go-daily, go-monthly, and go-yearly.
- init.nls: Setup functions
  - Spatial: GIS elements, parking spots, station, and virtual locations.
  - Agents: Residents with their properties and social network.
  - Objects: Households, cars, and destinations.
- tick.nls: Functions that are called periodically
  - Daily functions: Making (including deciding modality) trips, ending trips, and moving cars.
  - Monthly functions: Buy or sell subscriptions and cars, and share/update modality preferences.
  - Yearly functions: Age residents and move-out households and adult-aged children

The model and all supporting code are available publicly in the following Git repository, with full commit history available: https://github.com/EwoutH/SEN9120-ABC.

# 5. Model verification

In the verification phase of building a model, the modeller checks if the conceptualised model has been implemented correctly. It is important that the relevant entities and relationships from the conceptual model are translated into the computational model correctly so it is trustworthy and provides useful insights into the system that is studied. Therefore, the verification of a model involves testing the computational implementation to verify that the code accurately reflects the conceptual model and that the simulation is realistic (Railsback & Grimm, 2019).

The implementation of several variables, distributions, and functions of agents was verified by tracking individual agent behaviour and values. Furthermore, interaction testing and multi-agent testing was applied to make sure the computational output was in accordance with the conceptualised model. Most tests were done by using the command centre in Netlogo, but some implementations were verified more thoroughly by actively monitoring sets of agents in the interface of the model repeatedly. This was done to verify if the correct number of residents receive cars or subscriptions, if children move out at the right age, if the age gap between parents and children is realistic, and if the social network spreads information correctly. Verification methods and their results for different inputs are described in Verification table of Appendix D.

Furthermore, the initialised values of some dependent variables were verified by using unit testing via PyNetlogo to ensure stable and realistic behaviour in the model runs. An elaboration on this verification process is given in Appendix E.

# 6. Experiments

The model behaviour is tested by running experiments and analysing the gathered metrics. First, the experimental design will be presented, then the results are reported and discussed.

## Design

Three different policy interventions are tested with experiments. While a full-factorial design would have been interesting to test all possible configurations and measure interaction effect, this was computationally too expensive, taking up $3^3 = 27$ runs. Therefore, an experimental design was set up, with five different experiments, all using two magnitudes of the policy intervention. With a default scenario that is shared between all, this resulted in 1 + 5 * 2 = 11 experiment runs.

Each experiment is run for 60 months (five years). This proved enough time for the system to stabilize and provided a long enough run time for the longest model cycles (the yearly movement of households) to be measured completely. For each run, 10 replications were done to include the stochastic variation of the distributions and choice chances. This also shows the extent of path dependency. For example, some residents choose an unusual travel mode or start with a subscription and stick with it for some time.

While more runs would have been ideal, 10 was the maximum computationally feasible and proved for most KPIs in most experiments to be statistically significant compared to runs with other input values.

Ideally, scenarios would also be interesting to examine, combining those again with all the policy options would require days if not weeks on a compute cluster and engineering time to get all the initialisation and data gathering properly working. So, this is left for future research.

The input values for the five experiments are listed below. The first three only vary one policy lever and the last two vary a combination of levers.

*Stimulate shared cars*
Experimental values:

- Default option: there are 8 available shared cars in the neighbourhood.
- Option 1: there are 32 shared cars in the neighbourhood.
- Option 2: there are 128 shared cars in the neighbourhood.

*Paid parking*
Experimental values:

- Default option: parking is free.
- Option 1: Parking costs 93,60 euros per year (7,80 euros per month).
- Option 2: Parking costs 93,60 euros per quarter (31,20 euros per month).

*Remove parking spots*

Experimental values:

- Default option: no parking spaces are removed.
- Option 1: 20% of the parking spaces are removed.
- Option 2: 40% of the parking spaces are removed (making the parking norm 1.0).

*Parking package*

Combining the options from *paid parking* and *remove parking spots* to create a combined parking policy package.

- Default option: parking is free and no spaces are removed.
- Option 1: parking costs 22 euros per month and 20% of the parking spaces are removed.
- Option 2: parking costs 93 euros per month and 40% of the parking spaces are removed.

*Full package*

Combining all three policy options.

- Default option: 8 shared cars, parking is free and no spaces are removed.
- Option 1: 32 shared cars, parking costs 22 euros p.m. and 20% of parking spaces are removed.
- Option 2: 128 shared cars, parking costs 93 euros p.m. and 40% of parking spaces are removed.

## Results

In this subsection, the results of the performed experiments are presented and analysed. In each line graph, the time is represented on the horizontal axis in months and the KPI value is on the vertical axis. The blue line is the default scenario, the orange line is the first (moderate) policy option, and the green line represents the second (strong) policy option. The line is the mean over the 10 replications and the shaded area represents the 95% confidence interval.

First, the dynamic behaviour will be presented and discussed. This explains how the KPIs develop over time in the model. Almost all results contain some “teeth” in their curves. These are introduced by the influx of new households moving in, which happens only once a year (every 12 months). Finally, an overview of all experiment results together in the final timestep is provided in a boxplot.

## Dynamic behaviour

In the first experiment, the number of shared cars varies from the default of 8 to 32 and 128.

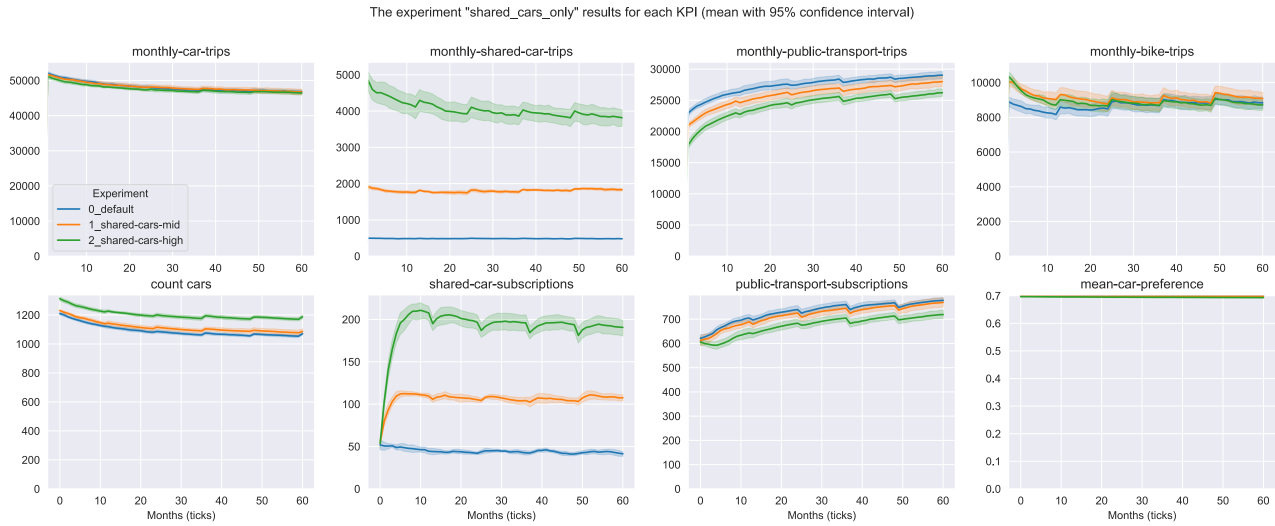


*Figure 6-1. Results of shared cars experiment.*

The results of this experiment indicate that the use of shared cars has increased up to a certain limit. The first 32 cars get almost fully utilised to the theoretical limit (31 days * 32 cars * 2 trips/day/car = 1984 trips), but the 128 do not get utilised even half at the last tick. Furthermore, it becomes clear that shared cars tend to substitute public transportation trips more often than car or bike trips.

With the increase in shared car use, the total number of cars has increased, meaning that more shared cars were placed than private cars were replaced. Finally, a gradual decrease in shared car trips over time is noticeable. This could be attributed to the formation of new habits for other modalities that are more frequently used, and residents' tendency to forget about the availability of shared car options.

These findings suggest that shared cars may provide a viable alternative to public transportation, but they may not necessarily replace private car ownership.

In the second experiment, the monthly price of a parking permit varies from the default of zero to 93,60 euros per year (current tariff for a permit in the city centre of Ede), to 93,60 euros per quarter (comparable with the tariff in some neighbourhoods in Utrecht).

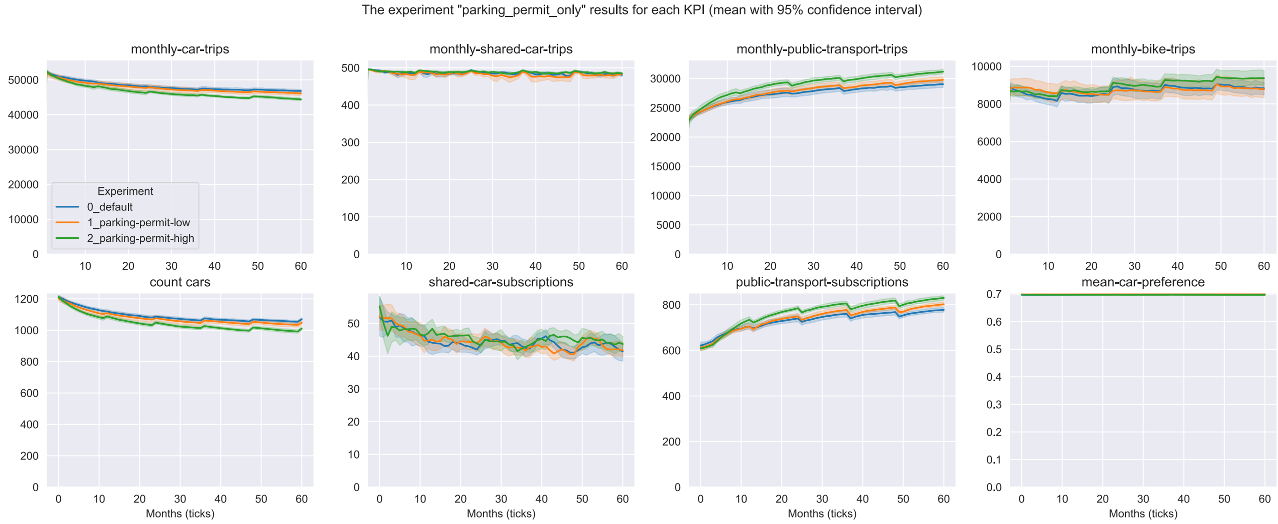


*Figure 6-2. Results of parking permit experiment.*

The graph shows that no meaningful results were achieved by this policy. However, the boxplot in Figure 6-6 demonstrates a very slight but statistically significant reduction in monthly car trips and car count, as well as a slight increase in public transport trips and subscriptions. These effects are small. Additionally, it is noticeable that the number of shared car trips does not increase; rather, it is capped at its theoretical limit of 492 trips per month (considering eight shared cars). All shared cars are almost always fully utilized in the base scenario.

The third policy lever varies the removal of 0%, 20% and 40% of the parking spots.

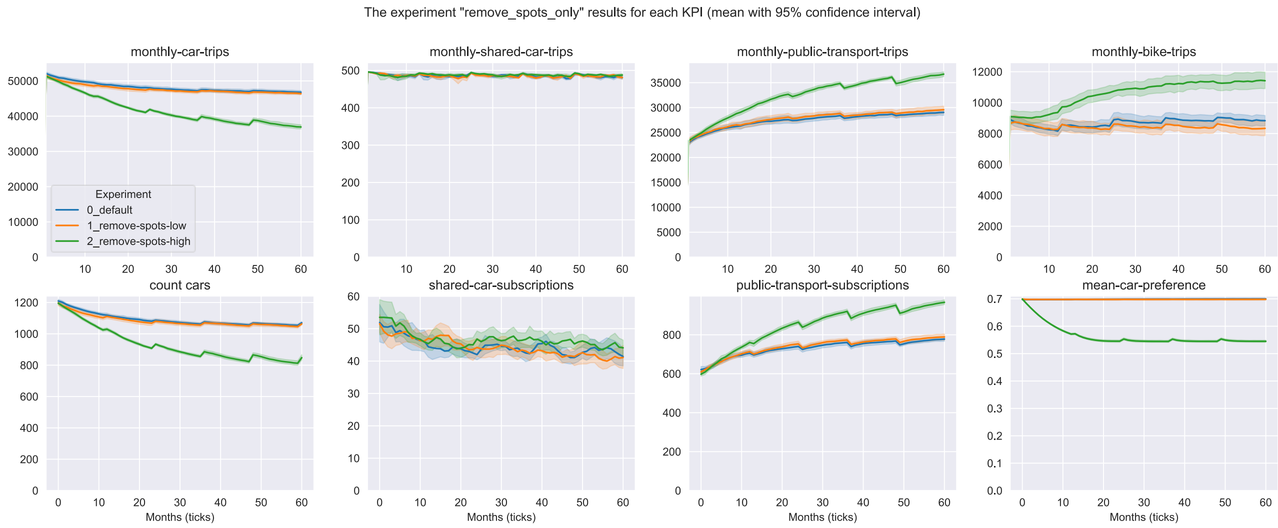


*Figure 6-3. Results of removing parking spots experiment.*

From this experiment, notably, removing 20% of the parking spots has almost no effect. This implies that there are at least 20% more parking spots than needed (given the current model initialisation and limitations), and can be removed and used for other purposes (which can provide other external benefits and shift modality preferences, as discussed in the conceptual model).

When 40% of the parking spots are removed, the car count and monthly car trips all decrease. Furthermore, both public transport and bike trips increase by approximately equal percentages. Both public transport and bikes take over the transportation demand.

Combining the two parking policies: Nothing, 20% spots removed and 22 euro permit, 40% spots removed and 93 euro permit.


*Figure 6-4. Results of the parking package experiment.*

When combining the parking policies in a single package, it can be observed that removing 20% of the spots and introducing a small parking tariff has almost no effect. Therefore, there is not a large interaction effect between those two options. The second and stronger policy package is more effective. Notably, while the number of cars decreases to the same level as with removing spots on its own, this level is reached faster and the mean car preference also stabilised higher. This implies that some people get rid of their cars because they do not find them financially attractive anymore and some because there are not enough parking spaces. This reduces the continued fight over parking spaces. For policymakers, it can be interesting to investigate further which combination of these two options creates the least resistance.

Finally, the number of shared cars, permit price and removal of parking spaces are all combined.

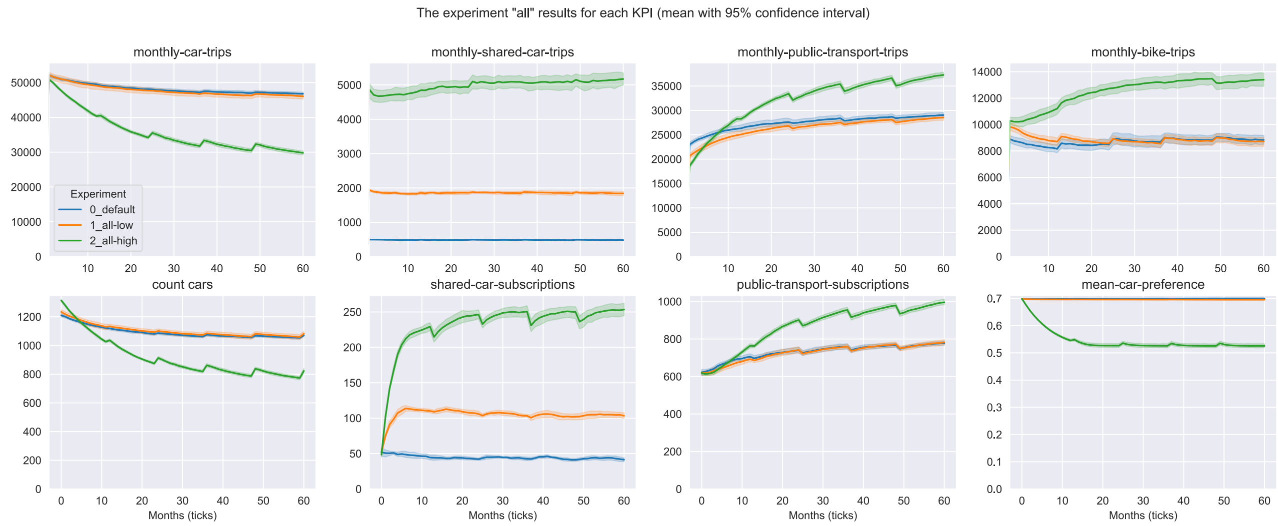


*Figure 6-5. Results of the all-combined package experiment.*

Figure 6-5 shows that with the low option, the number of shared car trips increases significantly, but the other KPIs do not show significant change. The shared cars replace mainly trips taken otherwise by public transport. In the stronger package, all car parameters show significant decreases. The reduction in car trips is spread over all other modalities, they are not only replaced by shared cars. When including more external benefits in the model, such as noise reduction and more green space, this is most likely the best policy option.

### Static overview

Finally, to create a broad overview of the effects of each of the experiments on each of the KPIs, all are plotted together in a boxplot. The KPI values are shown on the last tick of each experiment.

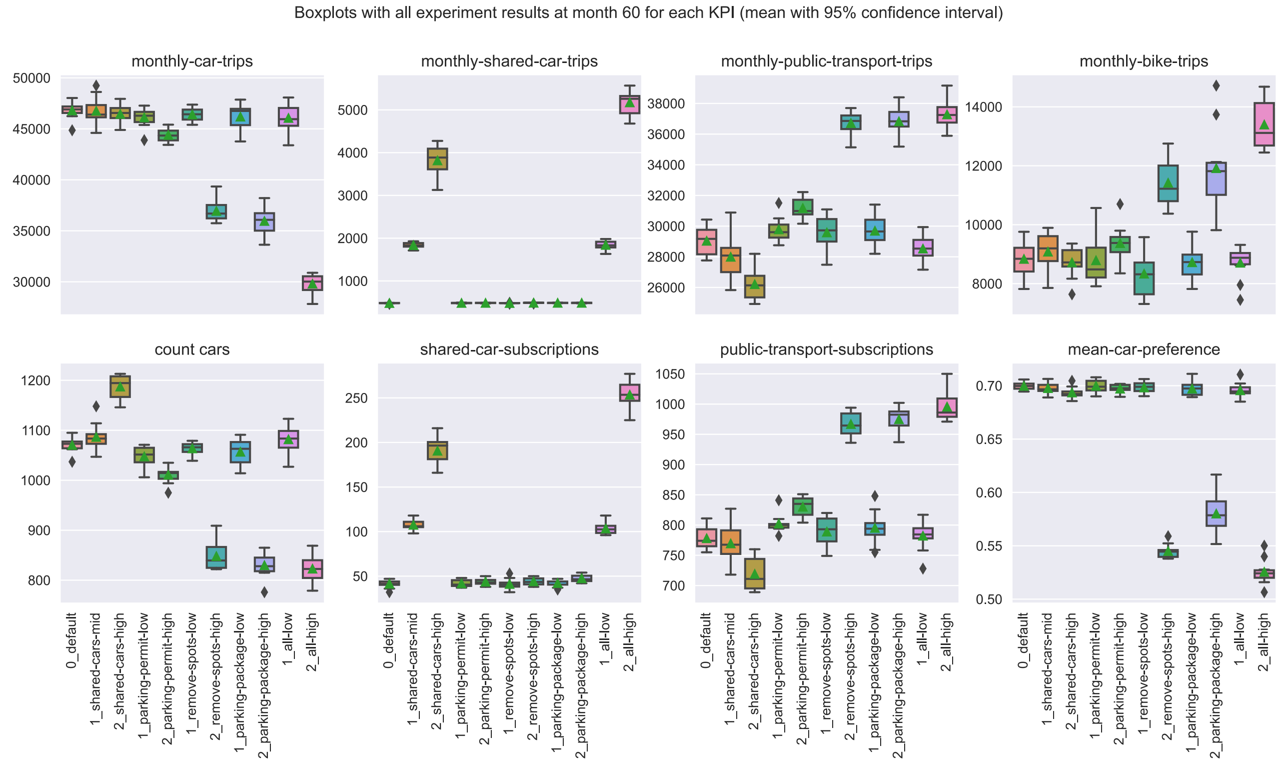


*Figure 6-6. Boxplot with all the experiment results at the last time step (month 60).*

Having all the policy options side by side shows the following insights:

- Removing a significant number of parking spots is essential to reduce the car count (considering model limitations).
- Up to 32 shared cars are used anyway, more need supporting policy options to be effective.
- When only introducing shared cars without other policy options, the total number of cars in the neighbourhood will likely rise.
- When the number of cars is reduced, all other modalities take a share of the trips, not only shared cars. Thus this can increase other external benefits, such as less noise, more space for playgrounds and nature etc.
- Introducing paid parking can be an alternative to prevent hassle over parking spaces.
- A combination of policies is most effective, but removing spots is essential for significant change.

# 7. Sensitivity

To gain further insight into the model behaviour, a sensitivity analysis is performed and reported in this section. This type of analysis can provide insights into which input parameters have a significant influence on the KPIs and, therefore, should be carefully calibrated and further researched. It creates insights into which external factors are responsible for changes in which KPIs and behaviour.

## Design

Ideally, a sensitivity analysis should examine both the independent effects of input variables and the interaction effects caused by select combinations of them. However, due to the long runtime of approximately one minute per month per replication and a computing budget of around 100 CPU core-hours, performing parameter sweeps over an n-dimensional input space, as possible with the EMA workbench (Kwakkel, 2017), was not feasible. Therefore, it was decided to focus on finding the independent sensitivity of input factors.

As the base scenario, we used the "1_all_low" experiment, which involved 32 shared cars, a 20% reduction in parking spaces, and a €93.60 per year parking permit fee. This was considered as the base case instead of the default scenario from the experiments because it was more in line with the sensitivities that would occur with most of the policy interventions. Ideally, multiple policy options should be tested on multiple scenarios, but this was not feasible due to computing time limitations.

In collaboration with the problem owners, nine variables were selected that were thought to either have a high sensitivity or be interesting to see the sensitivity of. The variables are listed in Table 7-1, along with their default values, the reduced (low) and increased (high) values that will be tested, and the relative change from the default value.

| Variable | Default | Low | High | Low change | High change | Change type |
|---|---|---|---|---|---|---|
| subscription-monthly-buy-sell-chance | 25 | 20 | 30 | -20% | 20% | +-20% from the default |
| preference-penalty-parking-outside-neighbourhood | 0,5 | 0,4 | 0,6 | -20% | 20% | |
| mean-value-of-time | 11,25 | 9,0 | 13,5 | -20% | 20% | |
| social-adoption-multiplier | 0,1 | 0,08 | 0,12 | -20% | 20% | |
| mean-preference-utility-tradeoff | 0,5 | 0,4 | 0,6 | -20% | 20% | +-10% from the range (= +-0.1) |
| initial-car-preference | 0,7 | 0,6 | 0,8 | -14% | 14% | |
| initial-shared-car-preference | 0,5 | 0,4 | 0,6 | -20% | 20% | |
| initial-bike-preference | 0,5 | 0,4 | 0,6 | -20% | 20% | |
| initial-public-transport-preference | 0,3 | 0,2 | 0,4 | -33% | 33% | |

*Table 7-1. Sensitivity analysis design.*

For the first four variables, which are all absolute numbers with a range of zero to infinity, a variation of +-20% from the default was applied. For the last five, a 10% variation from the total range was applied. In each case, the range was from zero to one and was thus varied with +- 0.1. They are more coefficients than absolute numbers. Therefore, it is more logical to vary them with this amount. Otherwise, the car preference would have varied more than the public-transport preference.

Finally, considering the 100-hour computing budget (which ran overnight), we decided to run the simulation for 48 months and use 12 replications for the default scenario, and six replications for each of the low and high values for each of the nine variables. This resulted in a total of 120 runs, each taking slightly less than an hour. Although simulating for longer would have been preferable, the 48-month period was sufficient to stabilise the model for the most part, and the results demonstrate that most variables have sufficiently narrow 95% confidence intervals to draw statistically significant conclusions.

# Results

For each input variable in the sensitivity analysis, the low and high results are plotted. The first five variables are presented in Figure 7-1, while the last four (which are all initial modality preferences) are shown in Figure 7-2.

In both figures, the results from the reference scenario are plotted in blue, while the increased (high) input values are shown in green, and the decreased (low) input values are displayed in orange. The dots represent the means, and the lines indicate the 95% confidence intervals.

This means that if the green value is higher than the blue one, there is a positive correlation between the varied input value and that KPI. Conversely, if the orange one is higher than the blue one, there is a negative correlation.

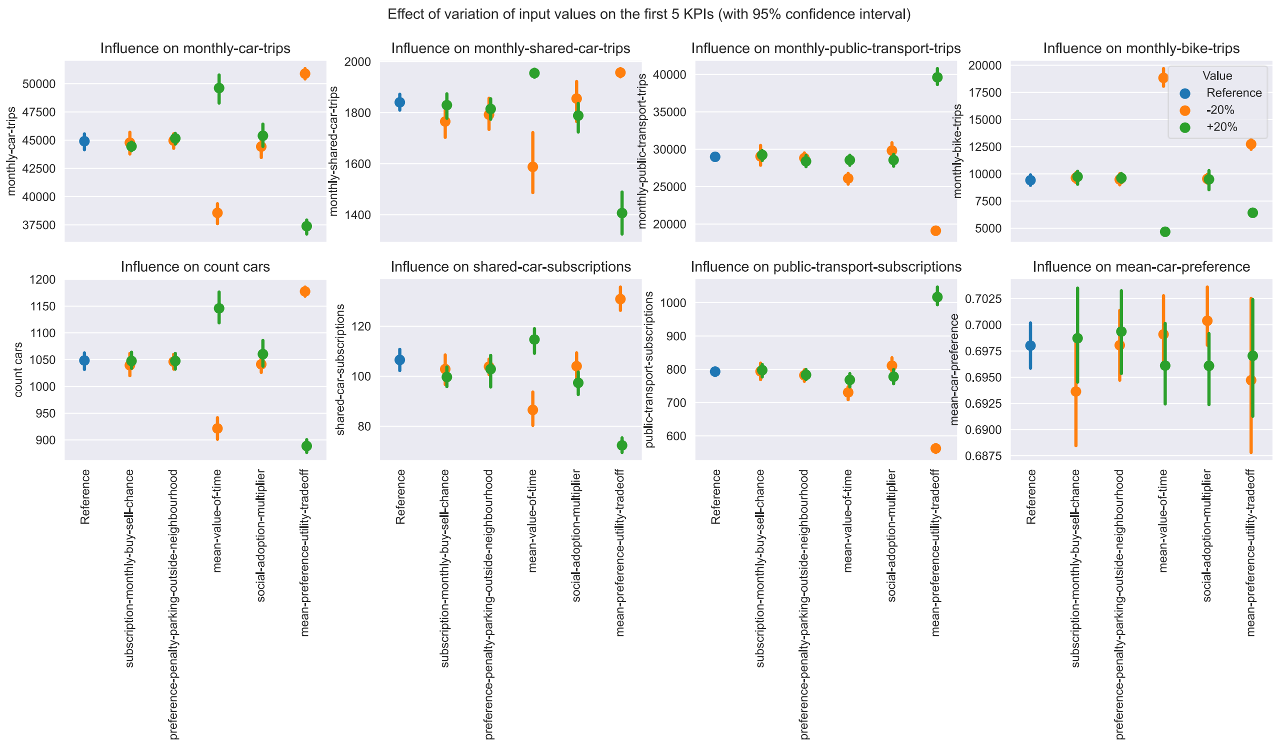


*Figure 7-1. Absolute results sensitivity analysis (part 1).*

The first part of the sensitivity analysis shows that the mean value of time and mean preference-utility trade-off are the most sensitive. A higher value of time shows more trips taken by car and shared car, a few less by public transport, and a large (50%) reduction in trips by bike. This is in line with the expected results; that the slower modalities are only worth it if you have a low value of time, and vice versa. The 20% lower value of time shows the opposite effect, with an almost 100% increase in bike trips taken.

The preference-utility trade-off shows the opposite relation. A high trade-off value means that the resident considers the utility of a modality for their trip more than their personal preferences, and vice versa. With an increase in this trade-off, car, shared car, and bike trips are reduced. But, the public transport trips increase. This implies that even though the utility of those modalities can be lower, this difference is smaller than the difference between public transport preference (0.3 on average) and the other modalities (0.5 / 0.7). So, a small focus on preference results in this scenario in more people taking public transport.

Furthermore, we see that the chance of people selling and buying their subscriptions, the social adoption multiplier, and the penalty for parking outside the neighbourhood are not very sensitive at the last tick of this configuration. The buy-sell chance might show a more interesting change in dynamic behaviour with the time to stabilise increasing or decreasing. The social adoption multiplier might become more sensitive when more external benefits are added to the model. Finally, the penalty for parking outside the neighbourhood is simply not relevant in this scenario, because with only 20% of the parking spots removed, there is no significant shortage of parking spots yet.

Beside the changes in absolute values, the relative increases and decreases are also plotted and normalised to the reference scenario. These plots can be found in the appendix in Figure 10-5. Normalised sensitivity (part 1). The sensitivity results for the last four variables (the four initial modality preferences), are presented in Figure 7-2.

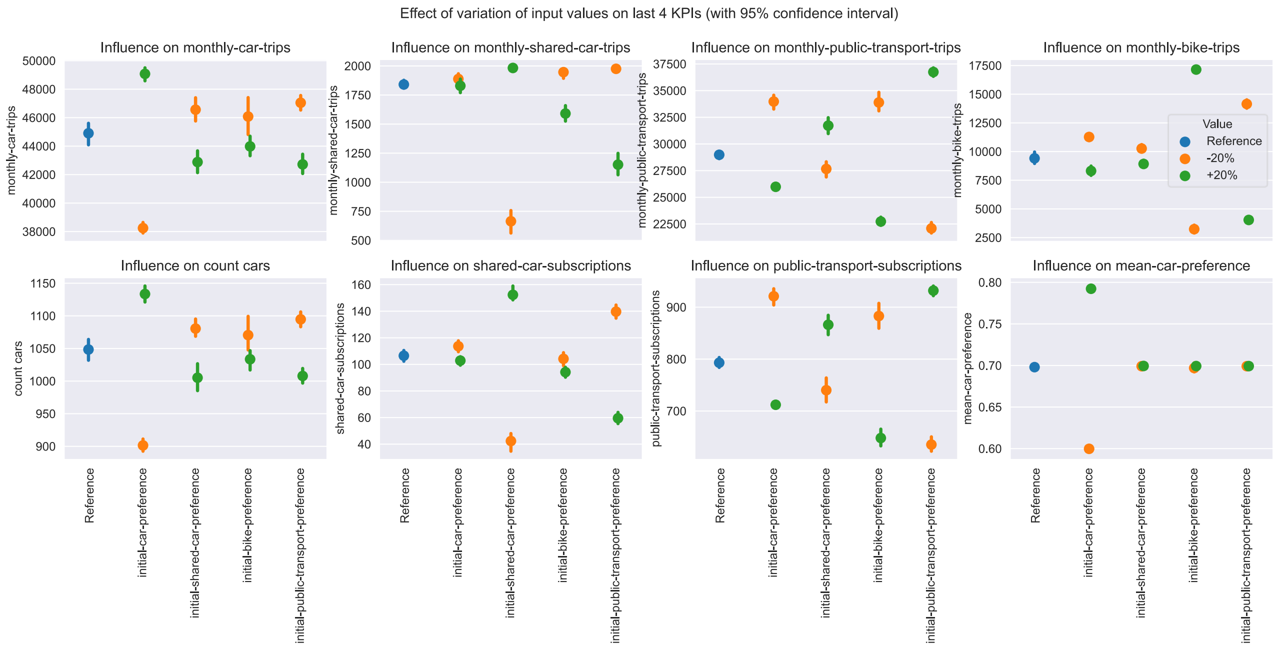


*Figure 7-2. Absolute results sensitivity analysis (part 2).*

The initial bike preference proved most sensitive, with an increase from roughly 10 thousand to 17 thousand trips when increased from 0.5 to 0.6, and an almost 70% decrease to around 3 thousand when lowered to 0.4. Since cycling is free but takes the longest time, a higher preference for it proves it can be influenced by the value of time and the preference-utility trade-off, but also by just preferring it. An interesting experiment that can be done in future research, is modifying the bike preference seasonally to see what happens to trips, car ownership, and subscriptions. It would show the adaptability and dynamic behaviour of the system.

All the other initial preferences are also quite sensitive, at least on their own modality. The shared car preference shows that with the 32 cars, they are mostly utilized, except when the initial preference for them is lowered to 0.4, then it more than halves. In lesser extent, increased preference for public transport or cycling also decreases shared car usage.

It can be noticed that when biking becomes more popular, public transport takes the biggest hit. But, when shared cars become more popular, public transport also slightly increases. This implies that people who sell their car in favour of shared cars, also use public transport more.

The relative sensitivity can again be viewed in the appendix, in Figure 10-6.

In conclusion, the value of time, preference-utility trade-off and initial modality preferences prove to be most sensitive in this scenario. The subscription buy-sell chance likely only has influence on the speed of adoption and not on the level it stabilises. Additionally, the social adoption multiplier is not yet relevant enough because there is only one external benefit. This is the penalty for parking outside the neighbourhood, which is not very sensitive in this scenario because there is no significant shortage of parking spaces.

# 8. Model validation

The model validation reviews if the outcomes and behaviours determined by the model are consistent with behaviours in the real world. In this section we will compare some of the model behaviours with reality and discuss whether they align or not.

Half of the KPIs are the number of trips taken with each modality. So, it is interesting to investigate if the distribution of modalities for the trips in the base scenario (without policy interventions) roughly aligns with real world values.

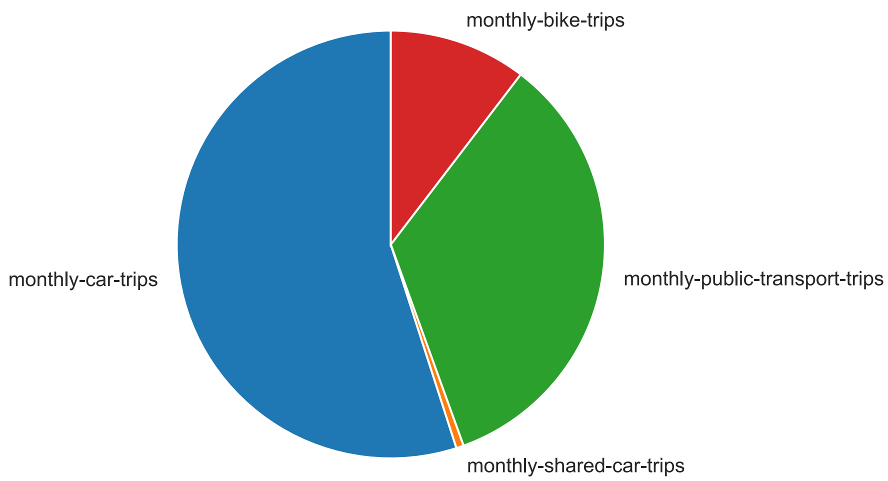


*Figure 8-1. Average monthly trips made with each modality in the default scenario.*

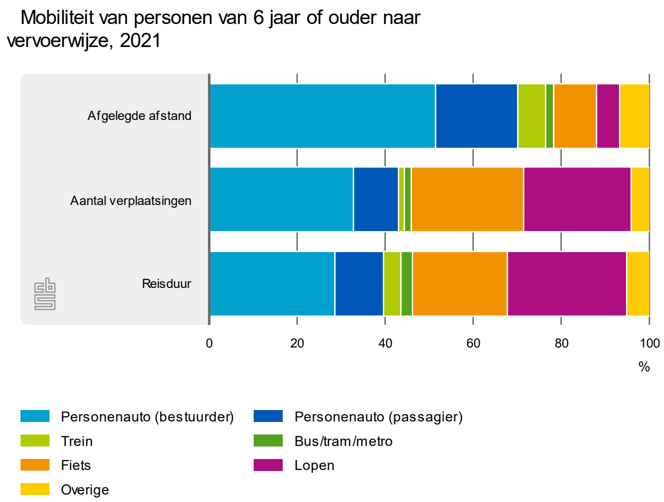


*Figure 8-2. Number of trips, distance and duration travelled for with each modality for all and work trips. From (CBS, n.d.).*

As shown, the number of trips taken by public transport is larger than in reality. The number of trips by bike is lower in the model, but since only consider larger movements are considered (on average, 8 hours / 44 km for work and 2.5 hours / 22 km for other trips), this could be accurate. The walking modality therefore can also be ignored, since people are not expected to walk such distances. Car trips seem to be in the right ballpark, especially considering that in a residential neighbourhood the car will be more dominant than in a city centre. Shared car trips are unfortunately not measured. In conclusion, the unrealistically high share in public transport should be investigated further.

# 9. Discussion & Conclusion

In this final section the limitations of the model and analysis are discussed. Furthermore, the concluding remarks of the report are delineated and next steps in future research are suggested.

## Limitations

The model build has some noteworthy limitations. Additionally, the experiments and analysis performed have limitations that should be highlighted. Most of them are to do with the scope of the project or the way the system is decomposed.

### Model limitations

The model is limited mainly by the available time to design, implement, validate, and test the model. Therefore, choices have been made about what to include and what not. Some design choices also have limitations to them. The following limitations were identified:

- Very limited external benefits are implemented. Currently only parking outside of the neighbourhood is seen as disadvantage. Converting parking spots to green spaces or playgrounds, cars causing noise and road hazards, and health benefits from cycling could be implemented as external factors. These factors would cause interesting emergent behaviour, when residents get rid of their cars, quality of life and therewith perceptions could improve. These could also be measured as separate KPIs.
- Currently, residents do not have positive or negative experiences during their commutes, except for rare events such as when they are unable to park their car. The inclusion of a built-in failure chance for each modality (traffic, cancelled train, unavailable shared car, broken bike) could influence preferences and provide additional incentives to break a habit.
- Taking into consideration the two aforementioned limitations, modality preferences only diffuse currently, except for car preferences. Consequently, the social spreading of preferences only causes the model to stabilise towards a more homogeneous population.
- The decision-making processes of residents can be hyper-rational in certain scenarios, such as when considering the purchase or sale of subscriptions or cars. However, they can also be purely chance based. Despite careful consideration, these choices may not perfectly reflect real-world decision-making behaviour.
- Residents make a fixed number and type of trips, including at most one work trip and one other trip each day. These trips are always single-purpose, and do not include preferences for other destinations.
- Transportation demand is currently static. In the real world, there would be some level of demand-modality elasticity when worse modalities are available.
- Households are currently an empty construct, serving only to provide a population to share experiences with. At present, there is no sharing of resources (such as cars or subscriptions) between households, no acquisition of resources between households, and no travelling together or sharing of destinations.

- Children do not play a role in this model. While it is logical that they do not use shared cars themselves, they would influence the modalities and destinations of their parents, for example, by requiring transportation to school.
- Many of the values are based on random distributions and are independent of each other. Although these have been thoughtfully constructed, there would realistically be correlations between modality preferences and the value of time, for example.
- Social networks currently do not change after initialisation.
- Destinations currently do not change over time.
- Costs do not change over time.
- The model has a long runtime, taking approximately 1 minute per month on a modern CPU core. This equates to around one hour for a 5-year run. Most processing time is taken up by the complex decision-making processes between modalities, which need to occur for each trip and for each resident every day. This limits the iteration speed and the number of experiments that can be performed in a given timeframe.

### Analysis limitations

The analysis of the model is also limited in several ways, primarily due to CPU time constraints and the limited scope of the project.

- Extreme value tests have not been performed. While regular sensitivity analysis has been conducted, testing some variables to their limits until the model breaks, and then examining how and why it breaks, could be useful.
- The experimental design has limited interaction effects. Although two packages of policies have been tested, not all combinations have been explored. Additionally, policies have not been tested under different thematic scenarios or external factors, which could provide insight into the robustness of different policies.
- No interaction effects have been studied in the sensitivity analysis. The input variables that were varied were only varied on their own, and not in combination with other variables to measure interaction effects between them. This could be achieved through parameter sweeps over an N-dimensional input space.

## Concluding remarks

This paper aimed to reveal the emergent patterns after implementing different transitional policies that discourage private car ownership and use by building an ABM for the neighbourhood of ENKA Ede. The policies that were implemented in the model for the experiments are the stimulation of shared cars, introduction of parking fees, and removal of parking spaces. To test the emergent effect of these policies, mild and drastic version of these were implemented as well as combinations of the policies. As follows the research question of this paper can be answered according to the model experiment results. The research question is restated below.

*'What is the emergent effect of implementing transitional policies that discourage private car ownership and use, on modality choice behaviour, vehicle ownership, and resistance in ENKA Ede?'*

Firstly, from the results it becomes clear that an increase in the number of shared cars in ENKA has no effect on the number of times privately owned cars are chosen for a trip. Furthermore, it increases the total amount of cars in the neighbourhood. The implementation of shared cars does not incentivise residents to sell their car and extra cars (shared) are added to the neighbourhood. When this is the only policy that is implemented, there is a shift in modality choices from public transport to shared cars. But when, too many shared cars are added to the neighbourhood, their occupancy rate decreases. Next, the introduction of reasonable parking fees has no significant effects on modality choices, vehicle ownership or resistance when it is implemented exclusively.

The removal of parking spaces as a sole policy does not have any effect when only 20% of the parking spaces are removed. This means that these parking spaces can be removed without any resistance. However, when 40% of the parking spaces are removed in ENKA, the amount of residents that choose to travel by car decreases significantly. This removal also leads to a significant reduction of privately owned cars because the policy incentivises residents to sell their cars. Unfortunately, due to the lack of parking spaces, residents will have to park their car outside of the neighbourhood which causes some resistance in the first 12-16 months after policy intervention. The reduction of parking spots alone causes a shift in modality choices from private cars to public transport and bicycles.

The most effective way to achieve the desired emergent pattern in ENKA, described in section 2, is the implementation of the drastic version of all three policy interventions together. The policies together cause the highest measured reduction in private car use (≈ 40%) and car ownership (≈ 43%). Because the amount of shared cars is also increased, modality choices do not only shift towards public transport and bicycles, but also to shared cars. With the reduction of parking spots, there is also a larger support base for shared cars. This results in a higher occupancy rate when a large amount of shared cars are added in ENKA. Additionally, the parking fee policy stimulates residents to sell their car slightly faster. Therefore, the resistance caused by having to park outside the neighbourhood phases out quicker.

Finally, the sensitivity analysis has revealed that the outcomes of the policy interventions depend heavily on input variables such as residents' travel mode preferences, how much they value their travel time, and how rationally they choose their modality for each trip. However, it is important to note that the manipulation of initial variables does not always result in the expected emergent behaviour. For example, if only the initial preference towards shared cars is increased, residents sell their car more quickly, but then replace this modality with public transport and bicycles as well as shared cars. This behaviour is in line with the outcomes of the experiments.

## Future research

Based on the model limitations and conclusions, the most important following steps in future research and model iterations have been determined. Firstly, expanding the household object by adding behaviours will lead to more realistic emergent behaviour. Resources such as cars and discount subscriptions could be shared amongst household members. Moreover, household members should be able to travel together so they are making the same trip in one vehicle instead of only travelling separately. Another way the model should be improved is by adding more external benefits and disadvantages that influence a resident's modality preferences. Thusly, individual preferences will change more dynamically through feedback loops and therewith make the effect of continuous interactions between residents more interesting. Ultimately, adding more external factors will make the resistance and support for policy interventions more observable.

Because the emergent modality choice behaviour and vehicle ownership depend heavily on the initialisation of dependent variables, data collection is crucial. For correct initialisation it is most important to find out what the actual travel mode preferences of the residents in ENKA are. Secondly, it is important to learn how much money the residents are willing to spend on average to get to their destination more quickly. Lastly, the trade-off residents make between the most cost- and time efficient modality and their preferred modality, is important an important initial factor. This data could be collected through surveys. It is recommended that the interaction effects between these variables and the policy interventions are measured as well in future research.

Finally, despite the limitations of the model and analysis, after limited testing, the model already provided meaningful and actionable insights. Furthermore, while many input variables were sensitive, the model proved to be resilient and always converted to a stable state in the model test runs.

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# Appendix A.

## System decomposition mind map

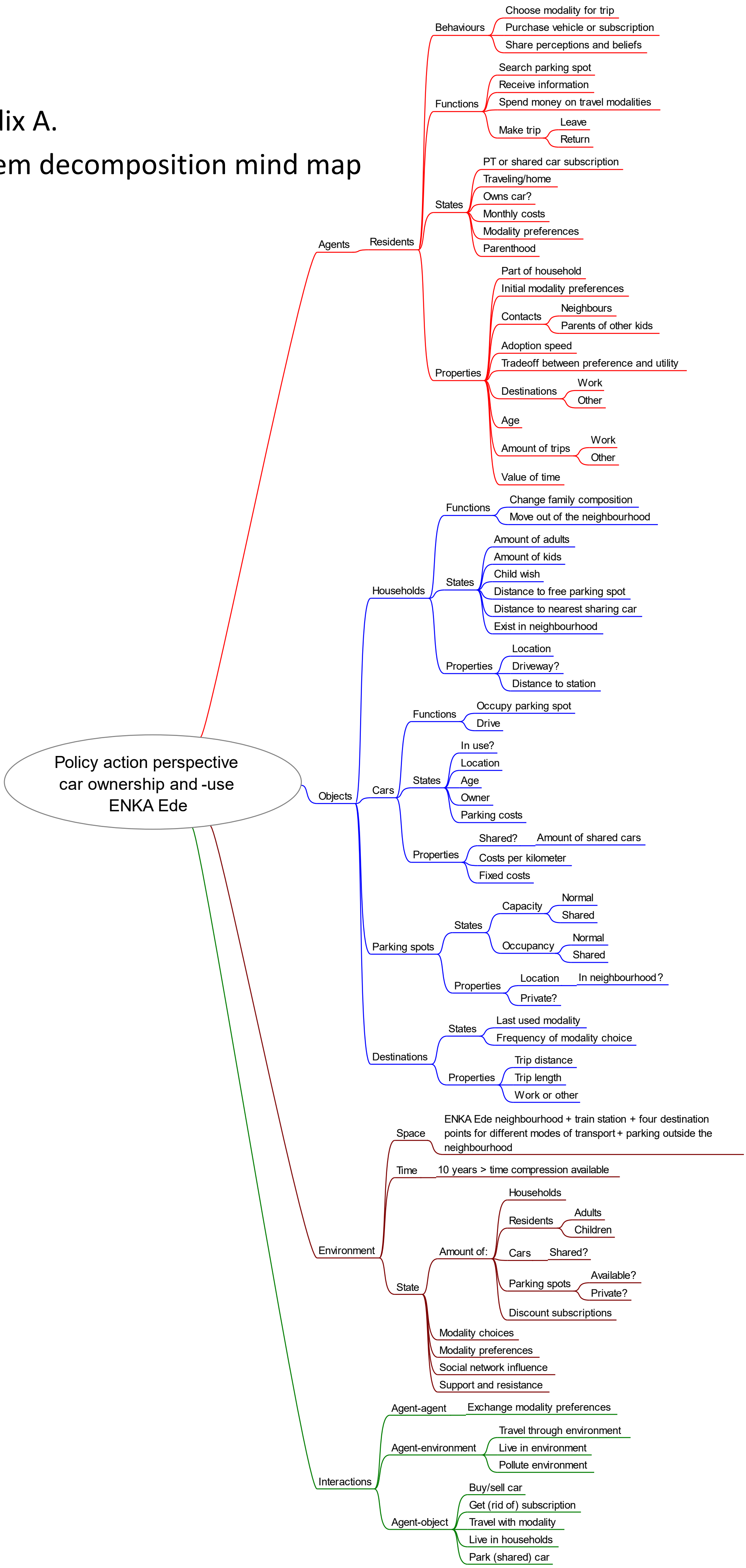


*Figure 10-1. Minc*

# Appendix B.

## Agent behaviour model

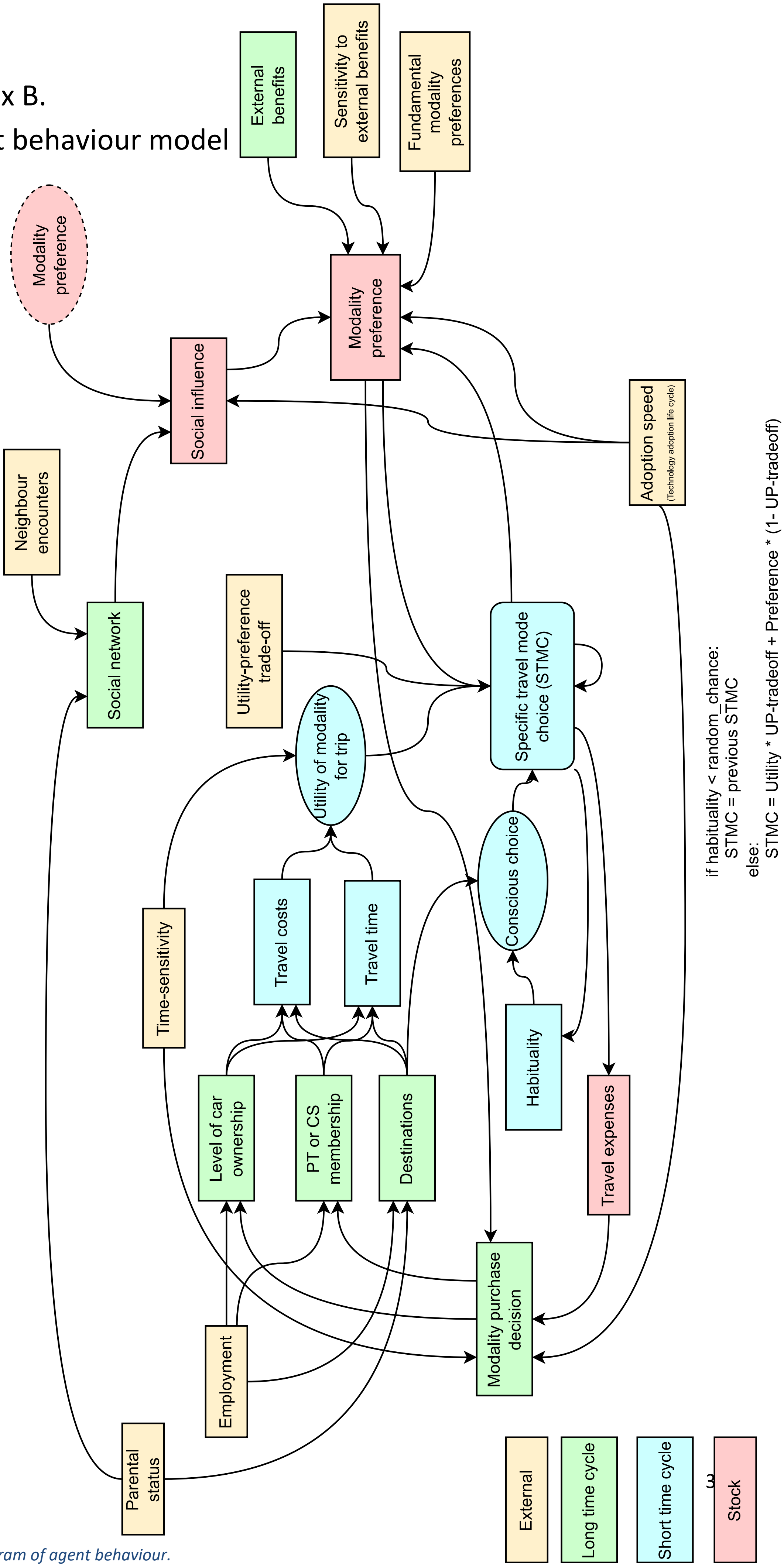


*Figure 10-2. Flow diagram of agent behaviour.*

# Appendix C. Table of independent variables

*Table 10-1. Independent variables.*

| | Variables | Range/value | Elaboration |
|---|---|---|---|
| *Global* | patch-distance | 0.018312102 | Distance of one patch in km |
| | walking-speed | 5 | |
| | day | 0-infinity | |
| | month | 0-infinity | |
| | year | 0-infinity | |
| | parking-dataset | gis dataset | Locations of parking spots with their capacity |
| | residential-dataset | gis dataset | |
| | grass-dataset | gis dataset | Green areas of the neighbourhood |
| | houses-dataset | gis dataset | House locations in the neighbourhood |
| | station-dataset | gis dataset | Location of the station |
| | projection | x | |
| | days-in-year | 0-infinity | |
| | virtual-locations | 0-2145 | Locations that represent destinations of residents |
| | pref-table | | |
| *Residents* | household-nr | 1-number of households | The household a resident belongs to |
| | age | 0-infinity | |
| | parent? | Boolean | Whether a resident has children |
| | owns-car? | Boolean | |
| | car-nr? | 0-number of cars | The specific car owned by a resident |
| | neighbours-contacts | 0-infinity | The amount of contacts of a resident in their neighbourhood |
| | parent-contacts | 0-infinity | The amount of other parents that are contacts of a resident |
| | work-destinations | 1 | The amount of destinations a resident travels to for work |
| | other-destinations | 3 | The amount of destinations a resident travels to leisurely |
| | min-monthly-costs | 0-infinity | The travel mode with the smallest effective costs for one destination of a resident |
| | min-monthly-costs-car | 0-infinity | The travel mode with the smallest effective costs for one destination of a resident when a car is available |
| | work-days | 0-infinity | The amount days a resident has to go to work in a week |
| | other-days | 0-infinity | The number of weekly trips for other reasons than work |
| | adoption-speed | 0-1 | Determines how impressionable residents are |

| | | | |
|---|---|---|---|
| | modality-preference | 0-1 | A table with updated values of personal modality preferences for each mode of transport |
| | preference-utility-tradeoff | 0-1 | A variable that determines whether residents focus more on the utility of their trip (higher value) or on their individual preferences (lower value) |
| | value-of-time | 0-infinity | Determines how much residents value their time in money |
| | total-car-costs | 0-infinity | The travel mode with the smallest monthly effective costs for one destination of a resident when a car is available, including the foxed monthly car costs |
| | total-costs | 0-infinity | The travel mode with the smallest monthly effective costs for one destination of a resident when no car is available |
| | modality-counter | 0-infinity | Counts the amount of trips made with each modality |
| | public-transport-subscription | Boolean | |
| | shared-car-subscription | Boolean | |
| | away? | Boolean | Whether a resident is traveling or not |
| *Households* | driveway | Boolean | |
| | distance-spot | 0-2145 | |
| | distance-station | 0-2145 | |
| | child-wish | 0-3 | Determines how many children might still be born into a household |
| *Cars* | owner | 0-number of residents | |
| | shared? | Boolean | |
| | age | 0-infinity | |
| | mileage | 0-infinity | |
| | in-use? | Boolean | |
| | current-driver | 0-number of residents | |
| *Parking spots* | capacity | gis dataset | |
| | shared-capacity | 0-number of shared cars | The capacity available for shared cars only |
| | private? | Boolean | Private driveway parking spots (left out of the scope of current model) |
| | household-nr | 0-number of households | The household a spot belongs to if it is private |
| | occupancy | 0-capacity | |
| | shared-occupancy | 0-number of shared cars | |
| | in-neighbourhood? | Boolean | Spots can be outside of the neighbourhood, when the occupancy in the neighbourhood reaches its maximum |
| *Patches* | station? | Boolean | |

# Appendix D. Verification table

*Table 10-2. Verification of several model implementations.*

| Description | How | Result | Code |
|---|---|---|---|
| Verified the number of contacts that residents have | Print with manual inspection | Numbers are withing expected range | `ask n-of 10 residents [type "Neighbours: " type count neighbours-contacts type ", parent contacts: " type parent-contacts type ", total: " print count (turtle-set neighbours-contacts parent-contacts)]` |
| Verified the distances drawn by the gamma distribution for both work and other trips | Print with manual inspection | Numbers are in the expected range and of approriate variance | `type "Trip distance: " print trip-distance`<br>`repeat 10 [create-destination false]` |
| Verified the table with the travel time and costs for each mode of transport for different residents | Print with manual inspection | Numbers of time and costs for the appropriate travel modes | `ask one-of residents [print work-destinations]` |
| Verified the minimum monthly cost counter with and without car as an option | Inspect two agents, one with a car available and one without | For both agents the car remained the cheapest option in the counter. Note: this does not included monthly car costs yet | |
| Verified that information is spread only to household members daily | Print with manual inspection | [(household 4360) (household 4360) (household 4360) (household 4360)] | `ask one-of residents [print [modality-preference] of residents with [household-nr = [household-nr] of myself]]` |
| Verified that subscriptions are used to discount travel costs | Print with manual inspection | | `let sample n-of 5 residents`<br>`print sample ask sample [set public-transport-subscription true]` |
| Verified that the modality-counter is succesfully reset | Print with manual inspection | Unexpected: The modality-preferences were reset to 0. This is because the wrong table was updated. Changing to the modality-counter table fixed this. | `ask resident 630 [reset-modality-counter]` |
| Verified that subscriptions are correctly bought | Print and inspect resident | See Figure 10-3. | `repeat 31 [go-daily]`<br>`inspect one-of residents with [table:get modality-counter "shared-car" >= 4]`<br>`ask resident 3263 [buy-sell-subscriptions]` |

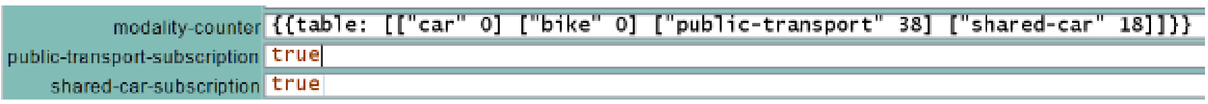


*Figure 10-3. Verification result of buying subscription.*

# Appendix E. Stabilisation of default scenario

Before experiments can be run it is beneficial to have a default scenario with stable behaviour. It would be strange if with no policy interventions, most of the population suddenly decides to take some other form of transport for example. It also reduces the need for model warm-up time, which can be (and is in our case) computationally very expensive.

The initial default scenario (blue in Figure 10-4) was not perfectly stable, as the number of public transport subscription increased sharply and the car count decreased significantly, among other effect.

Therefore, a number of experiments where done to get the base scenario stable. Using 5 replications for each experiment, 25 months were simulated and KPIs were gathered each month. The following experiments were performed:

- Changing nothing (blue)
- Increasing the value of time from €8.75/h to €12.50/h (orange)
- Halving the fixed monthly car costs from €257 to €128
- Decreasing the public transport speed from 34.8 to 28.0 km/h

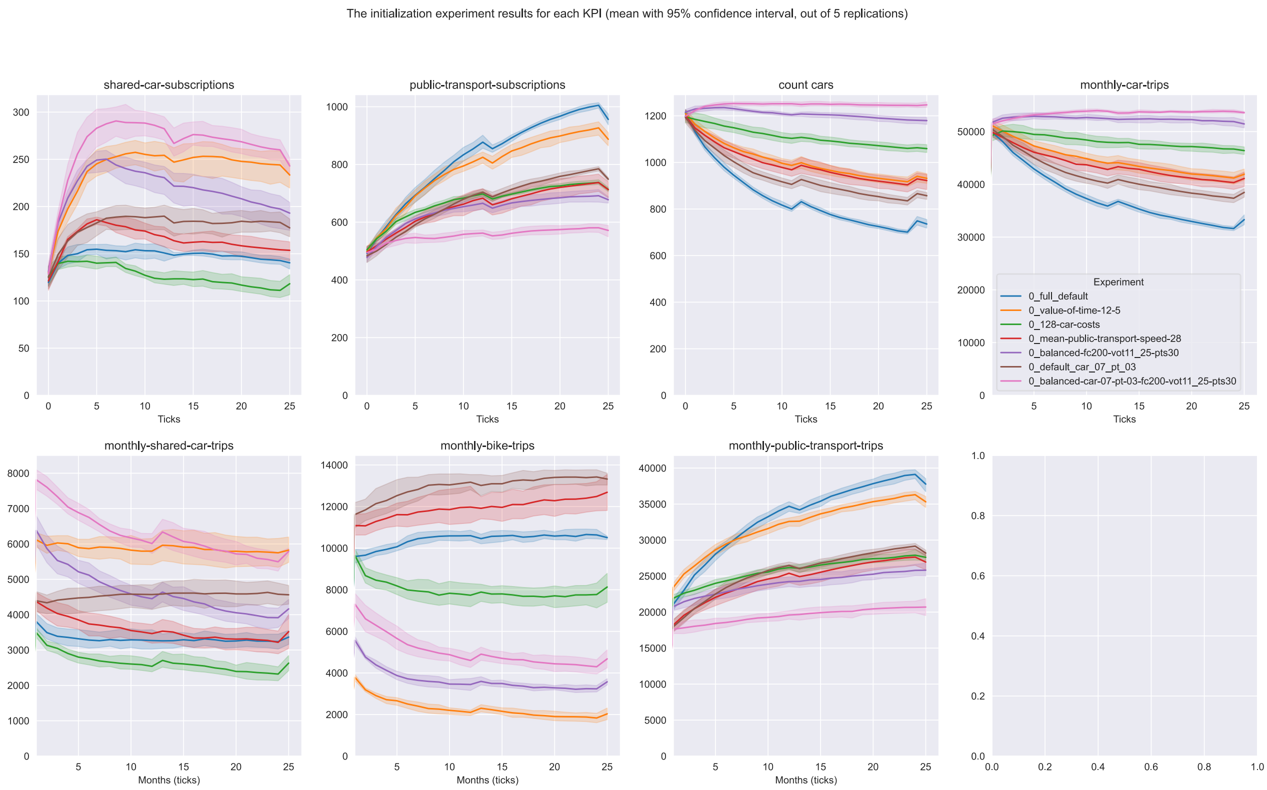


*Figure 10-4. Initialization experiment results for each KPI.*

All of those had some desired effect, so a balanced package was assembled combining those effects to a lesser extent. A value of time of €11.25/h, fixed monthly car costs of €200 and public transport speed of 30 km/h.

Purple in Figure 10-4, this package reached almost the desired effect, except still having some reduction in car count and some increase in public transport. To mitigate this, the mean car preference was increased to 0.7 and the mean public transport preference decreased to 0.3.

The resulting (pink) results show almost fully the desired behaviour. Only the initial subscription levels needed some adjustment, so the initial shared car subscription in increased from 5% to 8% and the initial public transport subscription from 20% to 25% (in Git commit 55a7485).

Note that this kind of stabilization comes with caveats. The goal is to create realistic and valid behaviour, not to conform the model to our desired behaviour. So, this kind of parameter tweaking should be done very cautiously.

For example, the average monthly car costs where reliably sourced from Nibud (2023) at €257 per month. Decreasing them would make not many sense, since this neighbourhood has more. The increase in value of time is more defendable, considering the neighbourhood, but should also be treated cautiously.

# Appendix F. Normalised sensitivity

Figure 10-5 and Figure 10-6 show the same results as presented in the Results, but then normalised to the reference scenario. A value of 1 means the KPI doubled from the base scenario, a value of 0.5 means it halved.

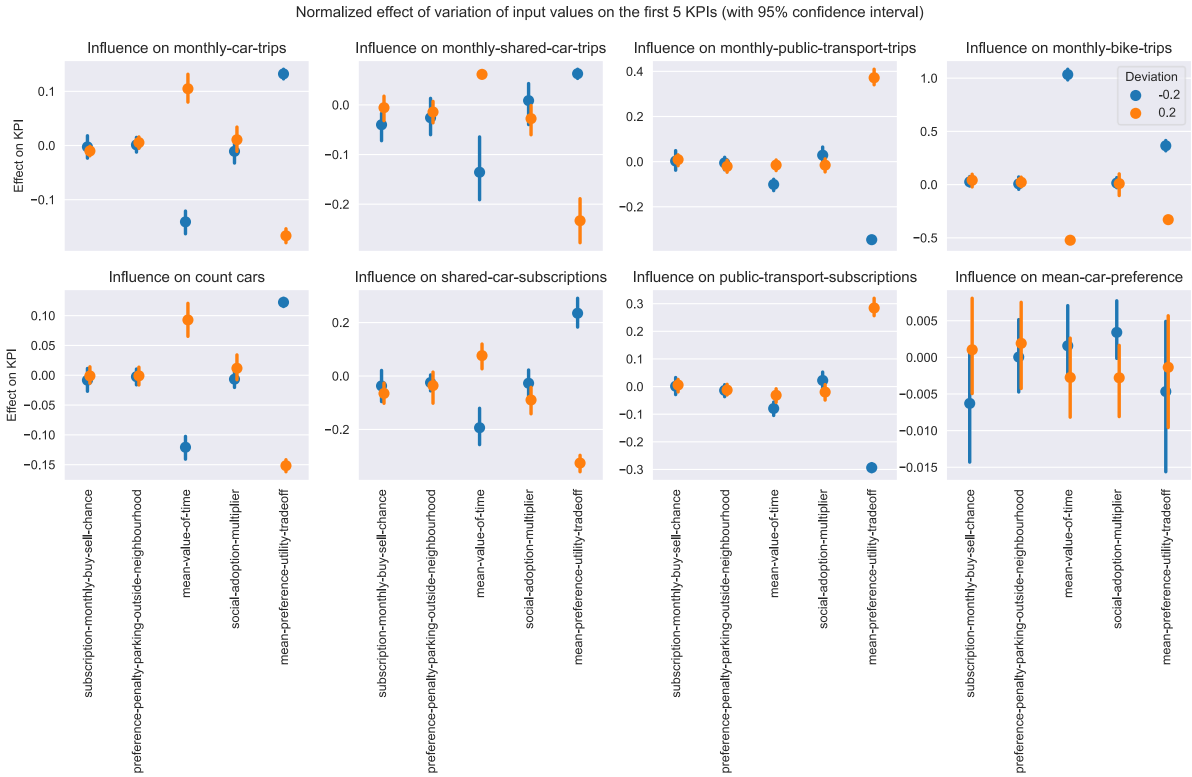


*Figure 10-5. Normalised sensitivity (part 1).*

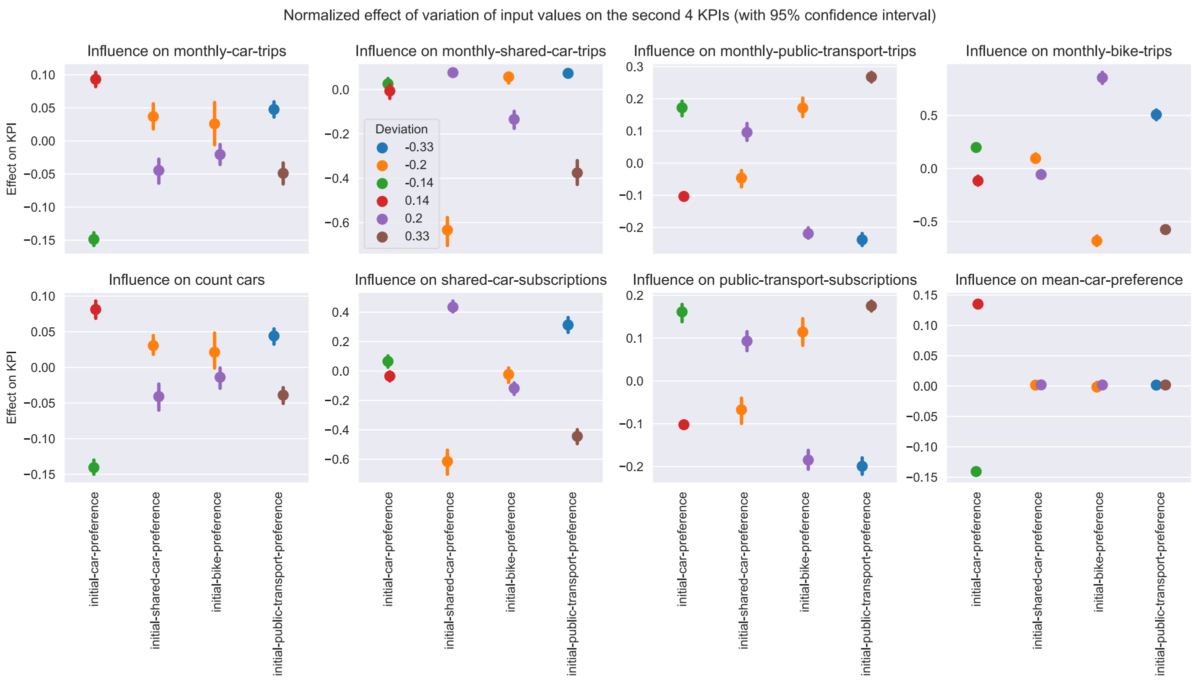


*Figure 10-6. Normalised sensitivity (part 2).*

# Appendix G. List of assumptions

**Households**

1. Households have 1-6 residents.
2. From 18 years old, teens have a X chance of moving out.
3. All households have at least 1 adult.
4. Households have a certain child wish that can be fulfilled from the start. If not, every year there is a X chance of households receiving a child. If the value is reached once, no more kids will be added to the households.
5. Households have a certain value that determines the chance to move each year.
6. Households have been 0-2 cars.
7. A household can have a car sharing subscription that can be used by all household members.
8. Households have between 0-2 private parking spaces.
9. Households acquire new modes of transport according to the mobility preferences of each member and the household budget that comprises the individual budgets of the adults in the households.
10. Within a household, transportation experiences are shared daily between members.
11. Households choose to acquire new modes of transport n* month.
12. Each household member has an X weight in the decision-making process within a household, determined by age.
13. Divorce is left out of the scope of this model.
14. Leave space for income differences.
15. Every household has X chance to have two adults and Y chance to have 1 adult.
16. Every household has an initial number of X children.

**Residents**

17. Residents can make between 0-3 trips per day.
18. A trip lasts between 1-3 ticks depending on the destination of the trip.
19. Residents have a certain preference towards their bike, public transport, sharing cars, and their private car.
20. Preferences get updated based on their own experiences, household experiences, and contact experiences.
21. Experiences are based on mobility satisfaction from trips.
22. If mobility satisfaction falls below a certain threshold, residents reconsider their transportation options.
23. The more extreme mobility satisfaction is (negative or positive), the more they share their experiences.
24. Residents have a random number of contacts in the neighbourhood who they share their experiences with and who share their experiences with them.
25. Residents have a list of destinations they might/have to visit.
26. Residents work 0-5 days a week (most adults full time).
27. Some residents work an X number of days per week from home.
28. The number of greenery/playgrounds/sport-areas, cars in the street, difficulties to find parking spaces, and sustainability in the neighbourhood influence the residential satisfaction of residents.

29. Safety is being left out of consideration.
30. All residents have the same inertia and influenceability, this global variable is included but can be converted into a distribution if data is available.
31. The chance of owning a car is not dependent on the household composition.
32. Networks of residents are neighbours and parents of children's friends.
33. Residents with children that are 12 years or younger have contacts through their children.
34. Up to a certain number of neighbours within a radius of 3 are selected as contacts for residents with a Poisson distribution.
35. Children’s peers that are considered in the model are max 1 year younger or older.
36. The chance of owning a car is determined by the modality preferences, when the preference towards cars is stronger that towards the other modes of transport, a resident gets a car in the beginning of the model.

**Destinations**

37. Destinations have a certain character (leisure or mandatory for example).
38. Mandatory destinations have a certain occurrence frequency.
39. Destinations can be in- or outside the physical boundaries of the neighbourhood.
40. All destinations have a travel time and cost for each mode of transport, depending on the distance.
41. Cycling is free.
42. The time and costs for public transport are calculated from Ede-centraal station to the destination.
43. Each resident has a certain travel time to Ede-centraal, depending on their proximity to it in the neighbourhood.
44. For car travel it doesn’t matter where you live in the neighbourhood.
45. Walking time to a sharing car is added to the total travel time when travelling by car.
46. Residents work, go to school, go to sport clubs, go to friends/family, and do groceries outside of the neighbourhood.
47. The only relevant travel within the neighbourhood is going to the station or sharing car locations.
48. Before an ‘other’ trip is made in a day, the work trips have been made for the day.
49. Trip time and costs are added for all modalities and then multiplied by time sensitivity to calculate effective costs for each trip and modality, therewith calculating the trip utility value.
50. Destinations are not updated monthly and remain unchanged throughout the model runs.

**Cars**

51. Car capacity is not considered.
52. A car is either private or shared.
53. A car is either in use or not.
54. Cars not in use have to be parked in a parking spot.
55. Cars have a certain age.
56. Cars have yearly maintenance and tax costs.
57. Older cars have more expensive maintenance costs that influence the mobility satisfaction.

58. Older cars cause more frustration, which impacts the mobility satisfaction.
59. Cars are parked on the closest available parking spot as the crow flies near a household.
60. If there is no parking spot available, the car is parked outside of the neighbourhood.
61. The further a car has to be parked the more frustration is caused for residents. More time is needed to search for an available spot.
62. The amount of shared cars in the neighbourhood is an input variable that is determined by policy.
63. Shared cars have a price per kilometre and a price per tick which is affected by residents subscriptions.
64. All shared cars have the same price units per kilometre and tick.
65. Different car brands and types are not considered, costs only depend on ages.
66. Costs of a new car are based on a regional average.
67. Cars have a very small chance to break down
68. Some cars are leased, if so, they are replaced after 4 years
69. Shared cars have designated parking spots.
70. For car costs the average of small-middle class cars are used.
71. Households can have more than one car but residents themselves can have up to one car only.
72. When a car has to be parked outside of the neighbourhood, a residents preference towards cars as modality decreases by a certain percentage, adjustable by slider.

**Other modes of transport**

73. There is no distinction between week and weekend public transport memberships nor costs.
74. Train, bus, tram and metro travel minutes are grouped together to find the mean travel speed of public transport.
75. Shared cars have designated spots they can park in which only they are allowed but also must park in. Optional: shared cars have designated spots but are also allowed to park in normal car spaces in the neighbourhood.
76. Subscriptions for shared-cars and public transport can be bought/owned simultaneously but are considered apart from one another.
77. When the amount of trips taken with either public transport or shared cars is larger than three, residents will consider buying a subscription that offers them a discount. The chance of them buying a subscription does not increase when the amount of trips with these modalities increases.

**Parking**

78. Parking spots are grouped in parking spaces with a certain capacity. Each parking space has a capacity of at least 1.
79. Some houses have their own private parking spots.
80. The amount of parking spots is an input variable that is determined by policy.
81. Refuelling and charging of shared cars is not considered.
82. Parking capacity in spots is updated daily, not after each individual trip.
83. When parking spaces are removed, a percentage is removed from the total parking capacity and not only from the capacity available for private cars. So the capacity of parking spots is

removed first in the model, thereafter a certain amount of shared cars is inserted into the neighbourhood with designated spots.

**Environment**

84. There are 3 ticks per day (morning, afternoon, and evening).
85. A year is modelled as n days (n to be determined, probably way less than 365).
86. Houses, parking spaces and green surfaces are modelled at representative locations.
87. Roads are ignored.
88. There are 3 different types of green surface (playgrounds, parks and sporting grounds).
89. The amount of green surfaces affects the residential satisfaction of the residents.
90. Green surfaces have a certain area in square metres.
91. The sustainability of a neighbourhood is determined by the emissions caused by residents, the mobility choices made, the amount of cars, and the amount of greenery in a neighbourhood.
92. There is a ratio between greenery and parking spots that changes throughout time.
93. The general satisfaction of people in the neighbourhood consists of the sum of the mobility satisfaction and residential satisfaction of all residents.
94. With policy, parking spots can be converted to green spaces and visa versa.
95. Residential satisfaction is also determined by the amount of available parking spaces, we assume a certain distribution of people wanting more parking spaces and people wanting less.
96. Weather conditions are not considered in modality choice.

**Choice model**

97. On a monthly basis residents choose to either buy or sell a car based on their costs of travel when a car is included in the options and when it is not. The utility-preference tradeoff weighs into this decision. So when a person owns a car but the non-car options are cheaper to the destinations of this person on a monthly basis, this person has a certain chance to sell the car.

**Numeric assumptions**

1. 88% chance of private ownership and 12% on lease (CBS, 2023a).
2. Particuliere autos rijden gemiddeld 10.000 km per jaar en lease autos 18.000 (CBS, 2023b).
3. Monthly costs for private cars are assumed to be 257 euros and costs per kilometre are assumed to be 23 cents (Nibud, 2023).
4. Hourly costs for shared cars are about 3 euros and 50 cents and costs per km are 30 cents (MyWheels, 2023).
5. Shared-car memberships cost 25 euros per month and provide a 25% discount on every trip (MyWheels, 2023).
6. Public transport membership provides 20% discount for work trips and 40% for other trips, this membership costs 26,70 euros per month (NS, 2023).
7. Average walking speed is 5 km/h.

**Numeric assumptions references**


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