TransportTransform documentation

This document outlines the model structure of the agent-based model (ABM) Transport_Transform according to the ODD+D (Overview, Design Concepts, Details, and Human Decision Making) developed by Grimm et al. (2020) and extended by Müller et al. (2013) with human decision-making.

The model code is available at: https://github.com/lujakockritz/TransportTransform

Table 1-1 below details the protocol and the respective guiding questions for each section as described by Müller et al. (2013).

Table 1-1 Guiding questions of the ODD+D protocol (based on Müller et al., 2013)

Structural elements	Example guiding questions
1. Overview	
1.1. Purpose	What is the purpose of the study?
1.2 Entities, State Variables and Scales	What kind of entities are in the model? By what attributes are these entities characterised?
1.3 Process Overview and Scheduling	What entity does what, and in what order?
2. Design Concepts	
2.1 Theoretical and Empirical Background	Which general concepts, theories, or hypotheses are underlying the model's design at the system level or the level(s) of the sub-model(s)?
2.2 Individual Decision-Making	What are the subjects and objects of the decision-making?
2.3 Learning Is individual or collective learning included in the decision process?	Is individual or collective learning included in the decision process?
2.4 Individual Sensing	What endogenous/exogenous state variables do individuals sense and consider in their decisions?
2.5 Individual Prediction	Which data do the agents use to predict future conditions?
2.6 Interaction	Are interactions among agents and entities assumed as direct or indirect? On what do the interactions depend?
2.7 Collectives	Do the individuals form or belong to aggregations that affect and are affected by the individuals?
2.8 Heterogeneity	Are the agents heterogeneous? If yes, which state variables and/or processes differ between the agents?
2.9 Stochasticity	What processes (including initialisation) are modelled by assuming they are random or partly random?
2.10 Observation	What data are collected from the ABM for testing, understanding and analysing it, and how and when are they collected?
3. Details	
3.1 Implementation Details	How has the model been implemented?
3.2 Initialisation	What is the initial state of the model world?
3.3 Input Data	Does the model use input from external sources, such as data files or other models to represent processes that change over time?
3.4 Sub models	What, in detail, are the sub-models that represent the processes listed in 'Process overview and scheduling'?

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1. Overview

The purpose of this ODD+D documentation is to provide an overview of the agent-based model (ABM) TransportTransform developed to model mode choice behaviour by transportation users. The entities, state variables, and scales of the model are discussed, along with the process overview and scheduling.

1.1. Purpose

The model simulates mode choice behavior in a transportation system, incorporating feedback related to affordances proxied by mode capacity. The model serves as a thinking tool to explore system dynamics rather than predict the future of mobility. It incorporates core mechanisms such as habit, occupancy, and social norms that influence an agent's decision-making process. The TransportTransform model analyzes user behavior in mobility, examining the interplay between environmental and social influences on decision-making. It encompasses interactions at the individual, meso, and system levels, with individuals representing mode users, the meso level capturing their social networks, and the system level encompassing mode choice and capacity.

1.2. Entities, State Variables, and Scales

The entities in the model are agents that represent travellers in the transportation system. The state variables in the model include an agent's mode preference, habit time, and mode occupancy.

Figure 1-1 outlines the classes in the model, TransportModel and UserAgent. These classes inherit properties from the mesa package developed in python.

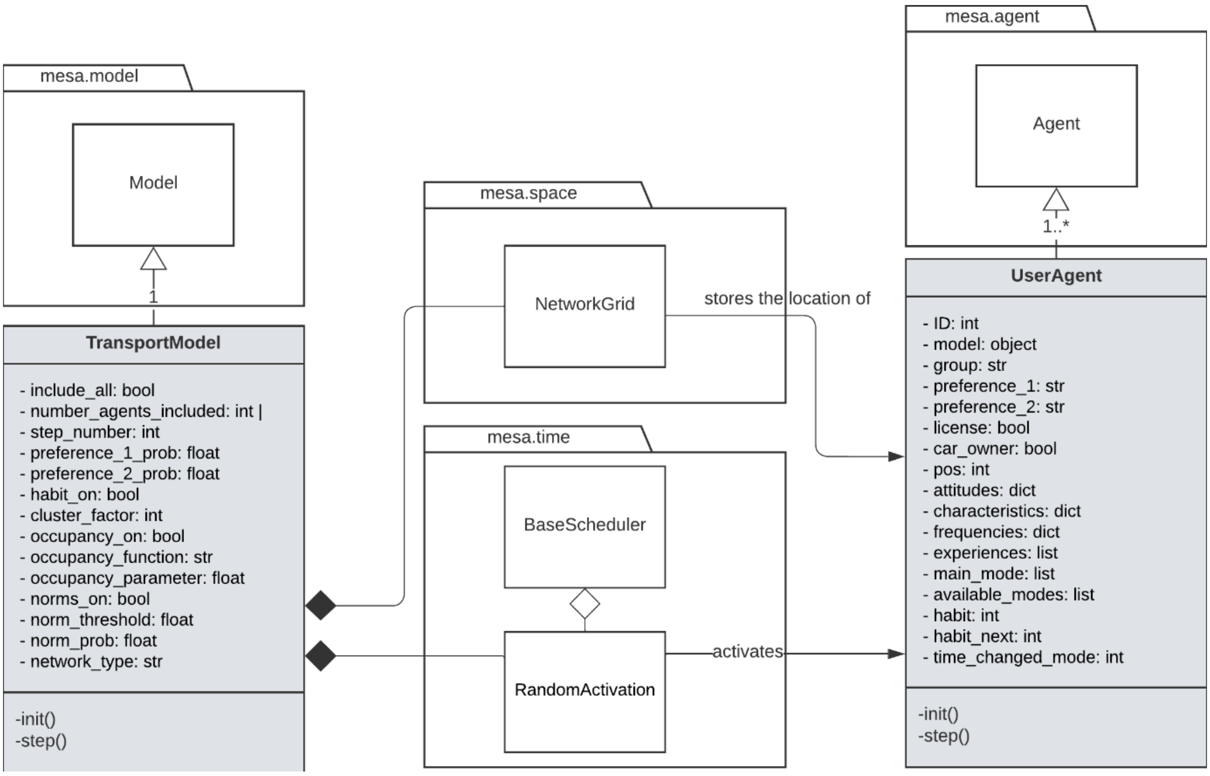

Figure 1-1 UML class diagram of the TransportTransform model. TransportModel and UserAgent inherit functions and properties from the mesa classes mesa.model and mesa.agent respectively. The TransportModel class interacts with the agents through the location of the agent in the networkGrid (a class of the mesa.space package) and by using RandomActivation (a class of the mesa.time package), which randomly activates every agent in every timestep.

- **Temporal and spatial scales**

TransportTransform is an abstract model; therefore, the model timescales are abstract and cannot directly translate to reality. Since there is a large number of agents in the dataset and due to the variability of the dataset when it comes to mode preferences, the spatial scale can be interpreted as an urban area in a German city. However, the spatial scales are represented by agents using the same transport system and their social ties; thus, they are not explicitly incorporated. As mentioned before, this model is not set to be indicative of the future German transportation system, but it is an analytical tool to explore different interaction mechanisms between agents and their environment.

1.3. Process overview and scheduling

The model simulates mode choice behaviour by initialising agents with mode preferences and habit times. Agents consider their mode preferences and the mode occupancy of the mode they previously chose when deciding. The habit, occupancy, and social norms mechanisms influence the decision-making process. The model is scheduled to run until a specified number of timesteps are completed.

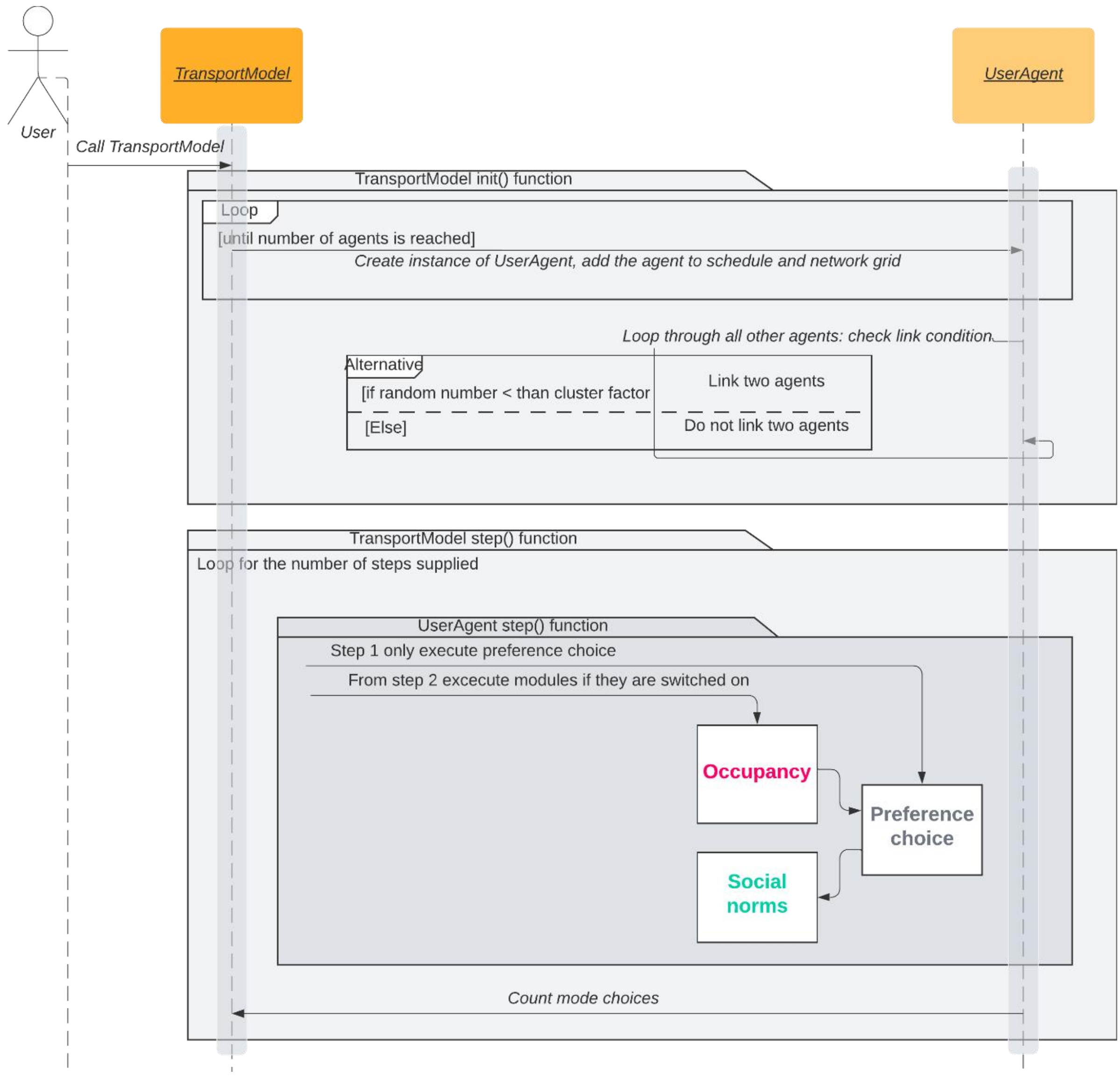

Figure 1-2 UML sequence diagram of the TransportTransform model. The Figure outlines the order in which steps in the model are performed. After a user calls the TransportTransform model, its inti function is started which create the number of agents specified by the user. Links between users are created based on probability related to a clustering factor specified by the user.

The follows the models step function which calls the agents step function per agent in a random order. Agents then execute only the preference choice module in step 1 or the other modules as specified by the users from step two on.

2. Design concepts

2.1. Theoretical and empirical background

The model is based on the feedback and affordances provided to the user in a transportation system as well as insights from social sciences on social norms. Eleven expert interviews informed model feedback development. The empirical data used was provided by Wolf & Schröder (2019) following a data-sharing agreement. These three foundations are elaborated below.

- **Theoretical foundation**

The study's theoretical foundation is based on the theory of affordances and social norms. The theory of affordances explores the dynamic relationship between individuals and their environment, considering both "internal (e.g., values, attitudes, personal norms, habits, and knowledge) [and] external (e.g., physical infrastructure, economic factors, and institutions)" variables " (Kaaronen, 2017, p. 2). The model implements an integrated approach that considers the interaction of internal and external factors based on the theory of affordances. Figure 2-1 outlines the theory of affordances. The study also acknowledges the role of social norms, which are defined as a "predominant [behavioural] pattern within a group, supported by a shared understanding of acceptable actions and sustained through social interactions within that group" (Nyborg et al., 2016, p. 42).

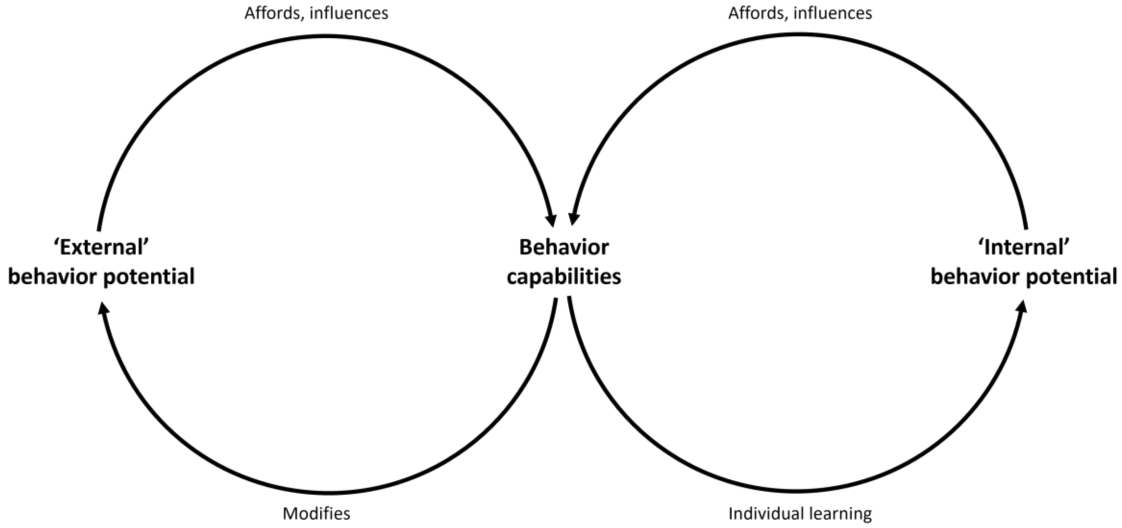

Figure 2-1 Affordance theory (own visualisation built on Kaaronen (2017) and Kaaronen and Strelkovskii (2020))

- **Researcher interviews**

The interview process involved three rounds of interviews: scoping, refining, and verifying. The interviewees were selected based on their expertise in the circularity of mobility, modelling, and conceptualising transformation. The interviews followed a semi-structured approach (Bryman, 2016), and an interview guide was developed. The interviewees were presented with a scenario visualisation (based on van den Berg et al., 2022) and asked to imagine the mobility system in a circular economy and identify interventions necessary for behaviour change.

- **Empirical data**

Empirical data is used to initialise the ABM to ensure consistency in the dataset concerning preferences for transportation modes. Following a data-sharing agreement, Wolf and Schröder (2019) provided a dataset with 5948 results from the survey they conducted in Germany on the connotative meanings of sustainability. This study incorporates the transport mode preferences (most, second-most, and third-most frequent modes), although the dataset records 248 data points for each respondent to ensure clarity of the relationships modelled. Not all data points were included. The process for excluding data points was due to the scope of the thesis. The scope of the thesis and the process for exclusion are described in the thesis. Once the thesis is available online, a link will be added to the GitHub repository where the code was published.

2.2. Individual decision-making

The base model can be run with two additional modules: **Occupancy** and **Social norms**. Figure 2-2 details the decision tree that the agent uses to determine their chosen transport mode depending on which modules are included in a particular run. Table 3-1 shows the module parameters. In the base model, agents decide using their mode preferences.

Base model (mode preference): Agents are initialised with a habit duration that stays constant throughout the model run; thus, they reconsider their habit after the same number of timesteps. When agents reach their moment to reconsider their mode, they set probabilities to all modes available based on their mode preference. Then the agent chooses a mode based on the set probabilities for their available modes.

Occupancy: This mechanism allows indirect interaction between agents. If 50% of all agents choose the same mode of transport, the agent will reconsider choosing a different mode. This choice can be overwritten through social norms.

Social norms: This mechanism allows direct interaction between agents. If 50% of an agent's neighbours have the same mode, the agent has an 80% chance of adopting it when reconsidering their current mode.

The parameters mentioned above can be varied.

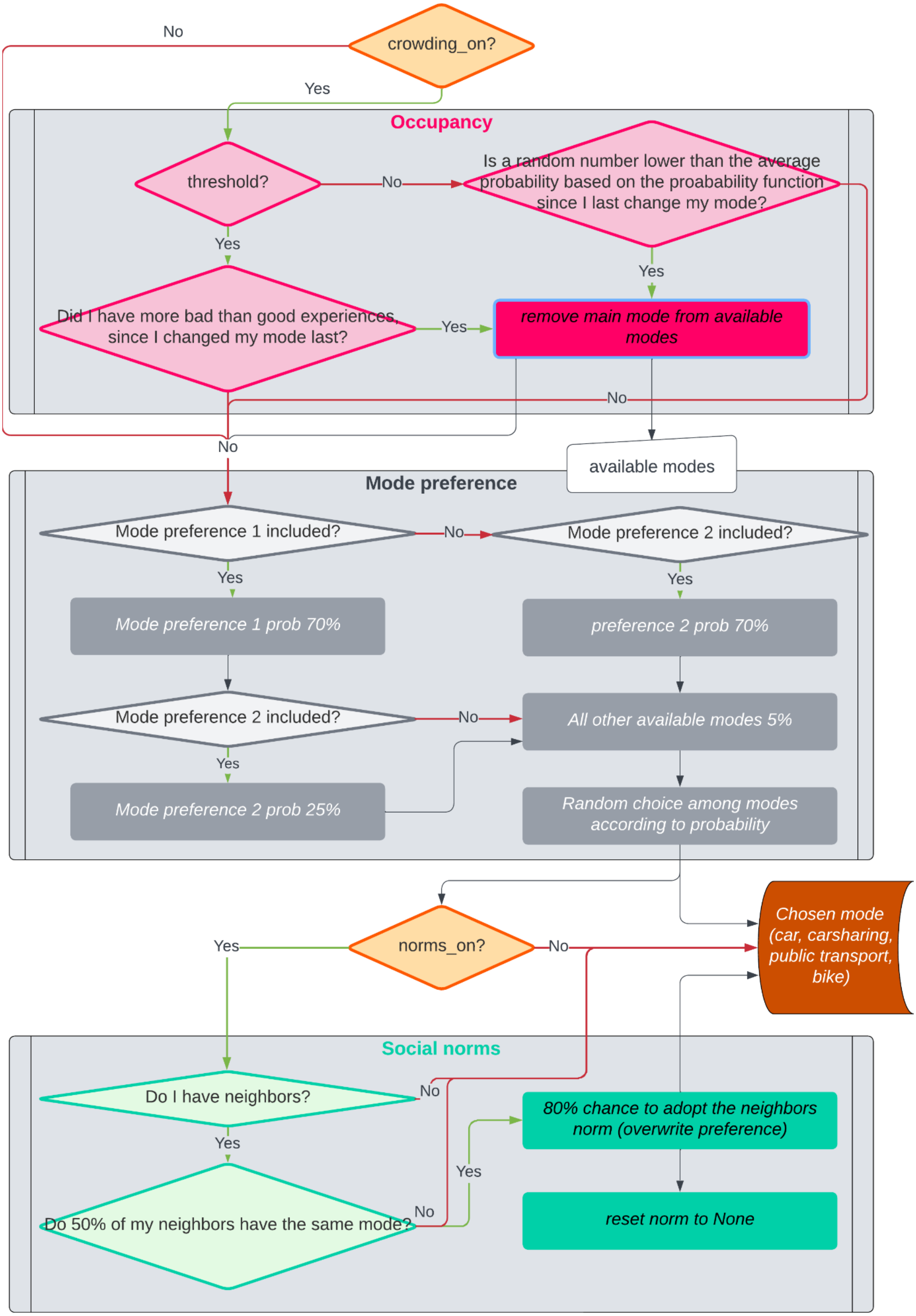

Figure 2-2 Agent decision tree of the TransportTransform model

2.3. Learning

Currently, there is no learning incorporated into the model. This means that variations in the model results depend on the stochasticity factors. Agents do not alter the characteristics, and the model variables are kept constant within a run. Adding learning to future model iterations is possible.

2.4. Individual Sensing

Figure 2-3 below shows what agents perceive in the model. They notice the occupancy of the mode that they choose. They also have perfect knowledge of the choices of all their neighbours, i.e. agents with whom they have a link.

The agent's perception, needs, decision-making process, and interaction with the affordances are detailed further in Figure 2-3. The figure shows that agents perceive both the mode they chose and the modes chosen by others within their social network. Agents' assets (car, license) determine their perceived options. The agent then evaluates their perceptions in concert with their mode preferences to first fulfil their need to choose their preferred modes. If there is a social norm in the agent's network, this choice is overwritten with the one dominant in their social network, provided that the agent has access to the mode instigated through the norm, such as owning a car. This choice is based on the theoretical insight that following social norms is often not directly related to individual preferences. The choice is also motivated by keeping the first version of the ABM as simple as possible.

Lastly, the agent will stick to their currently chosen mode as long as their habit time has not expired. Agents with shorter habit times are more willing to change than agents with longer ones. Accordingly, this simulates natural variety in the willingness to change within any population.

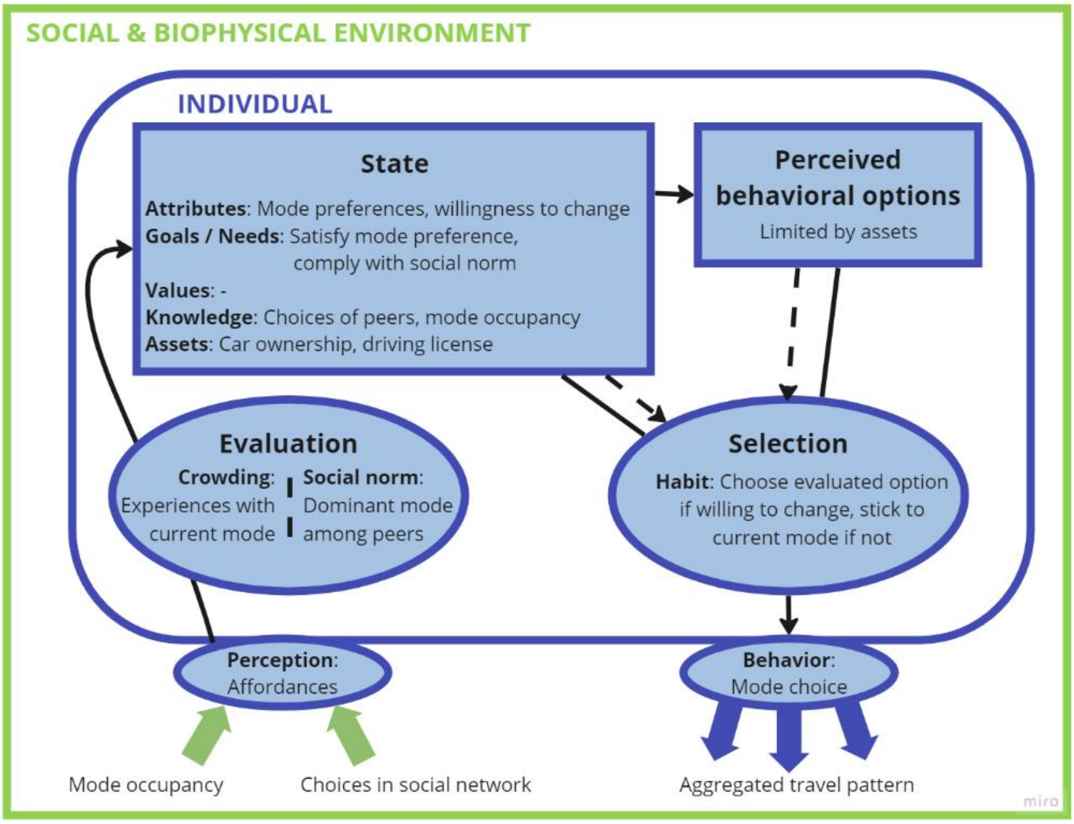

Figure 2-3 Agent perception and decision process overview according to the MoHuB framework developed by Schlüter et al. (2017)

2.5. Individual prediction

Agents do not predict future conditions; they only reflect upon the experiences they had in the past.

2.6. Interaction

The model includes indirect interaction between agents through the occupancy mechanism. Direct interaction in the model occurs through the social norms mechanism.

2.7. Collectives

While the agents are assigned to groups based on Wolf & Schröder (2019), the current iteration of the model does no use these grouping.

2.8. Heterogeneity

Agents are initialised with mode preferences and habit times that are heterogeneous. The discussion of the Master thesis for which this model was developed includes a variety of suggestions on how the heterogeneity of the model can be expanded, including suggestions based on the dataset used in this study. Once the thesis is available online, a link will be added to the GitHub repository where the code was published.

2.9. Stochasticity

2.9.1. Model initialisation

Stochasticity in the model initialisation lies in the selection of agents or in creating data stochastically. A generator is available with the above GitHub link to create random agents to run the model.

The links between agents are also created stochastically depending on an input parameter called clustering_factor.

2.9.2. Interactions

The base model implements stochasticity by giving probabilities to preference choices. This means there is a certain probability for preference one and two of the agents. The agent decision tree in Figure 2-2 shows how the probabilities are used within the model.

When the occupancy module is added, there is additional stochasticity. When a threshold function is used, there is no stochasticity, i.e. the agent will not choose the mode again if they had more negative than positive experiences since they last reconsidered their mode. With all other occupancy functions, there is additional probability. The probability curve depends on the function specified (linear, exponential, logarithmic, sigmoid).

2.10. Observations

Model observations are described and discussed in the Master thesis for which this model was developed. Once the thesis is available online, a link will be added to the GitHub repository where the code was published.

3. Details

3.1. Implementation details

The model is implemented in an agent-based modelling framework. The model developed in this study was initially built in NetLogo but later translated to Python to ensure flexibility with model development and data output and compatibility with future coupled models. The model structure was developed using the ABM Python package Mesa (Kazil et al., 2020) and the package to work with networks and graphs called NetworkX (Hagberg et al., 2008).

The data output structure, scenario, and sensitivity analysis code were inspired by the Knowledge Sharing Model by Pires et al. (2023)**,** whose code is publicly available via the ComSES database1. The class diagram in Figure 1-1 and the sequence diagram in Figure 1-2 have been added to this documentation since the Unified Modelling Language has been proposed to be particularly useful for ABM (Bersini, 2014).

Table 3-1 shows the standard parameters used in the simulations. These parameters were explored in a sensitivity analysis in the thesis, for which a link will be added to the GitHub repository linked above.

Table 3-1 Model parameter initial conditions

Parameter	Initial conditions
Base model	
Clustering level	10%
Highest preference probability	70%
Second highest preference probability	25%
Other mode probabilities	5%
Habit times	5 to 10
Occupancy Module	
Occupancy function	Threshold, linear, sigmoid
Occupancy level	50%
Social norms Module	
Threshold for norm change	50%
Probability of norm change	80%

3.2. Initialisations

Agents are initialised with mode preferences based on empirical data as described below and habit times that are randomly assigned.

3.3. Input data

Data for mode preference initialisation was taken from Wolf & Schröder's (2019) empirical study on the connotative meanings of sustainable mobility.

3.4. Sub models

The base model can be expanded with the Occupancy and Social Norms modules. The interaction is described above.

3.5. Intended Audience

The TransportTransform model is primarily intended for academic purposes, facilitating the exploration of data and relationships within the model. It can be used to inform policymaking or to review the effects of existing policies.

[1] https://www.comses.net/codebases/3fcbf222-fb89-499c-8859-82d48ac2b833/releases/1.0.0/

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