BELIEF DYNAMICS DRIVEN BY SOCIAL INFLUENCE

A social practice-based model of opinion adaption driven by intragroup interaction with application to transport mode choices.

Nena Roes
4290119
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Belief dynamics driven by social influence

A social practice-based model of belief adaption driven by intragroup interaction with application to transport mode choices

by

Nena Maria Josephina Roes

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Student number:	4290119
Dr. M.E. (Martijn) Warnier,	TU Delft, First supervisor and Chair
Prof. dr. ir. C.G. (Caspar) Chorus,	TU Delft, Second supervisor
MSc. R. (Rijk) Mercuur,	TU Delft, Advisor

Engineering and Policy Analysis,
Faculty of Technology, Policy and Management
TU Delft

Associated codes and models are available at `https://github.com/nenaroes`.

TU Delft Delft University of Technology

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EXECUTIVE SUMMARY

Agent-based modelling (ABM) is a widespread and commonly used technique for the understanding of social system behaviour. Despite ABM being a commonly used method for the analysis of complex social systems, simulated agents still can best be described as autistic before a specific set of social rules is ascribed to them. This discrepancy leads to model outcomes that can differ from reality. For improving agent-based models on this aspect, a social practice theory-based approach can be used as a theoretical framework. The main question to be researched is: *How does enabling agents to reason about others' beliefs on social practices affect dynamics of belief and behaviour formation as opposed to action adaption models, with respect to transport mode choices?*. By answering this question, the aim is to contribute to two related disciplines: (1) the field of multi-actor systems, with a focus on platform development and (2) the field of agent-based simulation, with the focus on improving the representation of agents with reality in order to explain human behaviour.

In order to achieve the set objectives, two agent-based models are designed within this study. In these agent-based models, within a group-setting agents have to form a preference towards one transport-mode (i.e., bus, bike or car). Though this is an individual consideration, these transport mode-choices can be influenced by the perception agents have on the opinion of other agents that they ought to be co-oriented to themselves. Subsequently, to shape this social awareness, agent beliefs are shaped by the awareness of social practices and the elements of these practices, as is taught by the social practice theory. As a result, the social interaction between agents translates into the model by agents being capable of adapting their beliefs towards the beliefs of other agents that they find to be co-oriented peers. Often, within the field of opinion dynamics this copying of properties of other agents is done under full information transparency. However, it can be questioned if this adequately represents reality as individuals can misjudge how others think and behave. Therefore, a second version of the model gives agents a restricted insight into other agents' properties through agent-specific theory of mind capability.

The two models created for this thesis distinguish themselves from the state of the art by using agent beliefs as the reference point agents compare themselves by. Usually within the transport domain, not beliefs but actions serve as this reference point. Therefore, the results of the simulation runs of the models with belief adaption are held against the typical macro behaviour produced by models with action adaption. Through comparing the outcomes in belief dynamics and transport mode shares, differences and similarities between belief-adaption, action-adaption and levels of insight on others internal system are perceived. Following from this comparison, it can be concluded that belief- and action-adaption models as implemented within this thesis, do not show significant differences in outcomes. This, because for both belief-adapting and action-adaption models clustering of beliefs appears to a higher degree as the simulation progresses. Also, shares of preferred transport modes find an equilibrium after which they stay constant. However, this similarity holds provided that there is full transparency in beliefs, values and travel satisfaction of other agents. When a restriction towards these insights is introduced by theory of mind capacities of agents, a change in social network connectivity leads to different results for both model versions. Where models with full information transparency (both belief- and action-adaption models) result in stronger consensus as the number of agents in the simulation increase, this is not the case for information transparency restricting models. Moreover, the theory of mind induced model thus presents agents staying closer to their personal beliefs. An increase in the similarity threshold responds the same to a including theory of mind capacity;. Thus, with full information transparency an increase in the similarity threshold leads to agents clustering their beliefs more easily towards the poles of the belief-space, which is not the case for the model with theory of mind restricting information transparency.

Alongside these model outcomes, multiple restrictions arise when these theoretical findings are taken back to the real world. one of these restrictions results from the sociality of agents within the models, which is not considered to be fully representative to reality. This, because agents can only interact when they are similar, can only increase their relation strength and in the ToM-included model cannot learn about each others beliefs, values or travel satisfaction and thus keep making the same misjudgements. Furthermore, the conclusions on similarity between belief-adaption models and action-adaption models depend on high-level hypotheses. Because action-adaption models vary in the behaviour they produce, combining findings on these models to more detailed hypotheses has not been not possible. However, because of these high-level hypotheses, the statements on both social comparison approaches being similar or not also only applies to high-level cases.

Despite these restrictions, the findings within this study contribute to both science and society. When considering the scientific contribution, especially the multi-actor system perspective of this thesis provides new insights. The theories embedded in this study appear to be adequate tools for modelling the influence of social interaction. Firstly, the social practice theory with belief adaption provides similar behaviour as state of the art work that rests on different theoretical framework. Secondly, the theory of mind provides different model outcomes and thus new insights, making it important for multi-actor systems to elaborate on the extend to which individuals have insight into the properties of others. When considering the societal contribution, the agent-based approach stands more central. Through this study, a step in the direction of better understanding social influence is set. This understanding can help policy makers finding the right measures to steer individuals in the desired direction. For example, considering the effect of group size large groups might need relatively less individual incentives to be steered in a desired direction because there is more social influence. When considering the effect of similarity threshold, a relatively homogeneous group might be directed to a wanted position via central policy, whereas a more heterogeneous group would need more individual incentives as beliefs converge less easy through social interaction.

Acknowledgements

I would very much like to thank my supervisors, as they helped me to take this thesis to the next level which I have very much appreciated. First of all I want to thank Rijk Mercuur, for being strict with me when I would come with new research ideas. The sentence "Yes, sounds interesting.. But if you choose one of these three directions, do you think that would still be interesting?" saved me from myself more than once. Then I would like to thank Martijn Warnier, for his very helpful feedback and for being his down to earth self. At the start of this journey Martijn told me "It is just a master thesis, nothing more nothing less", which became my mantra during the downs everyone gets to experience while writing a thesis. Also I want to thank Caspar Chorus, for bringing his expertise in both the transport- and opinion dynamics domain.

But besides these wonderful supervisors, I am sure the result would have been different if it was not for my mom, Maarten and my friends, who all have cheered for every victory, small or big.

Nena Roes
Delft, July 2019

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INTRODUCTION

"In reality, there is no such thing as absolute freedom.
The rules of social interaction determine one's freedom."

Eraldo Banovac

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1.1. RESEARCH PROBLEM

In the world around us, many physical objects are given meaning and purpose by human associations. Social systems provide a template that shapes our physical world into familiar patterns and perceptions. Social systems are embodied by individuals, which interact in time and space, have goals and preferences and behave accordingly (Page, 2008). A tool to help understand social systems is agent-based modelling (Gilbert, 2008). Agent-based modelling (ABM) can help explain and predict social systems, discover new unknowns and clarify core dynamics (Epstein, 2008).

Agents often do not give an adequate representation of human behaviour as there is a lack of a core ingredient: social constructs (Hollander & Wu, 2011). Dignum et al. (2015) argue for four constructs that are important foundations to human behaviour: social identity, norms, values and social practices. Mercuur (2018) zoomed-in on the latter, as social practice theory can help to map routinised, social and interconnected characteristics of behaviour, which leads to a better understanding of social phenomena. In this research, the same approach will be taken with regard to analysing social behaviour; through the lens of social practice theory.

At this point, due to an absence of social constructs in agents' default state, agents can be described as 'autistic' before a specific set of programmed social rules is designated to them (Kaminka, 2013). Every simulation requires the development of its own specific set of social rules for agents to follow. This is time-consuming and, above all, since best-practice adaptation is impeded, a good social representation of human behaviour is often not achieved. In order to move away from their autistic nature, Mercuur et al. (2018) created the Social Practice Agent (SoPrA) model, which lets agents follow logical rules that depict social practice theory for their decision-making. In aforementioned approach, agents implicitly or explicitly make decisions concerning social practices, based on their own perspective. This perspective is shaped by agent-specific beliefs. Agents' perception of the world is not only shaped by their personal values and beliefs, but also by the opinions of people they perceive as to be co-oriented. In other words, opinion dynamics (i.e., the (trans)formation of opinions realised through small-scale social interactions which eventually can lead to emergent behaviour) play an important role in the difficult task of exploring human behaviour. However, it is not yet known how the SoPrA would include social influence in the decision-making process. Social practice theory can provide tools that are required for agents to form a concrete perception of the private characteristics of other agents, when considering a specific set of alternatives.

Therefore, the aim of this thesis is to create a social practice framework that can function as a building block for ABM, where agents reflect on not only their own state, but also on their perception of co-oriented peers and adjust their beliefs accordingly. The agents will face a decision that triggers intentional decision-making. In other words, this study focuses on a 'concrete willingness to act', where individuals base their decision on values and knowledge, as opposed to the 'abstract willingness to act', where decisions result from habits (Preuss, 1991). A case study will provide a real-life complex situation which is known to be sensitive to social influence in order to explain the effects of social practice-constructs on the individual and group level (Gitelson & Kerstetter, 1995). The case used within this thesis arises from the transport domain, where a belief-oriented approach as provided by the social practice theory is uncommon. This, because within the transport domain social influence usually rests upon the comparison of actions. This makes it possible to compare outcomes of a belief-oriented approach to the typical macro behaviour of the state of the art which considered to be an action-oriented approach.

The opinion dynamics and behaviour of belief-adapting agents subjected to intra-group interaction will be captured in a conceptual framework and simulation model. This simulation model will be exploratory in nature and thus predictive questions are not included. By conceptualising and formalising these processes, the black box of agents' public- (visible actions) and private (internal beliefs) states caused by social influence can be captured.

1.2. RESEARCH GAP

Social systems and opinion-dynamics can be considered as a complex research field. Researchers addressing these topics cover a wide variety of disciplines, including psychology, sociology, computer science, statistical physics and econophysics. A lot is unknown about the causes of opinion-dynamics leading to polarisation, consensus or anarchy (Yu et al., 2016). There are multiple models that try to capture opinion dynamics (e.g. Gekle et al. (2005)) alongside many models and frameworks concerning social interaction and -influence (e.g. Goldspink et al. (2000)). Yet there are many aspects within these systems and their synergy that are underexposed. For example, the effect of certain social skills and the reference point for social comparison on opinion-dynamics. Furthermore, studies on opinion dynamics often concern a political case study with active persuasion, whereas day to day practices are rarely the centre of attention (Gekle et al., 2005). For social interaction studies, often competitive scenario's are used, such as game-theory related topics. In this study, these research gaps are addressed by analysing opinion dynamics in a simulation model where agents differ with the state of the art in their reference point for social comparison. As aforementioned, within the transport domain social influence often relies on comparing actions. However, social practice theory has a strong focus on beliefs, which will be used as the reference point for social comparison. There will be two versions of this model; one with and one without social skills leading to a certain degree of insight in other agents' beliefs, values and travel satisfaction. Furthermore, in this study, the social practice theory based designed conceptual framework will be implemented in a cooperative, non-persuasive setting. In Chapter 2 these high-level descriptions of the knowledge gaps are described in more detail.

1.3. RESEARCH QUESTIONS

This research aims to contribute to the reduction of the knowledge gaps as described in Chapter 1.2. In order to do so, the questions presented in this section are addressed in this research.

The main research question in this study is as follows:

How does enabling agents to reason about others' beliefs on social practices affect dynamics of belief and behaviour formation as opposed to action adaption models, with respect to transport mode choices?

This research question is divided into six sub questions:

SQ 1. How can transport mode decision-making be shaped as a social practice?

In order to design an ABM where agents are able to reason from a social practice perspective, first of all it is necessary to transform the travel mode decision into it's social practice form.

SQ 2. What is the typical macro behaviour of models where agents make predictions about other agents based on the *actions* of others?

In order to present differences in agent behaviour under different social comparison circumstances, it is necessary to have clear what the typical opinion dynamics and transport mode choices over time are in studies with behaviour as comparison material.

SQ 3. How can the realism of the agent-based model with a social influence component be evaluated?

A big challenge in social simulation studies lies within claims around its correspondence with reality. This sub-question addresses to what extend and how it is possible to ascertain that simulation models such as the one in this study, are a proper representation of reality.

SQ 4. How does belief-based social comparison affect social interaction and opinion-dynamics, compared to the behaviour-based social comparison?

This sub question aims to present the macro behaviour of models where agents compare themselves to others based on beliefs. How are opinion-dynamics and the resulting decisions made within these models similar or different? Social learning can cause a shift in beliefs, which might lead to individuals to hold similar beliefs even though they started with different view points (Acemoglu & Ozdaglar, 2011). This sub-question will analyse how these dynamics follow from social interactions.

SQ 5. How does limited information-transparency between agents influence opinion dynamics and agent behaviour?

This sub question analyses whether adding a theory of mind-capacity to agents and with this limiting insights in the beliefs, values and travel satisfaction of other agents, affect opinion-dynamics and consequently, agent transport-mode preferences.

SQ 6. How do different levels of connectivity within the social network influence opinion dynamics and agent behaviour?

For the simulation model created for this study, assumptions and initial parameter settings have been used to create a social environment for agents. Two of these variables creating the social environment are the group size and the threshold that determines when agents find themselves co-oriented enough to become part of their representative group. For this sub question, the effect of different values for these variables on the shift in beliefs of agents is studied.

1.4. METHODOLOGY

Insight into the behaviour and thus possibilities to steer the direction of grand challenges is often restrained by complex social phenomena (Goldspink et al., 2002). While behavioural science has its roots in disciplines such as psychology and sociology, insight provided into these social phenomena by methods such as computer simulation gain popularity as it can reveal emergent behaviour explaining higher level behaviour within complex systems. Furthermore, through simulation studies different theories on sociality can be tested, which can help to decide on different truths. However, concerns remain whether computer simulation is able to capture the complex nature of human behaviour, especially behaviour resulting from social interaction (Goldspink et al., 2002). More insight on how sociality can best be captured in simulation studies not only improves the quality of behavioural models, but can also contribute to rising the confidence in the legitimacy of computer models used for explaining social phenomena, found within almost every grand challenge that we are facing today.

In order to contribute to this development, multiple methods are used within this study. Four main parts within this methodology can be distinguished; a literature study, application of theories to the case study, the agent-based model with simulation runs and lastly an analysis of the results. Figure 1.1 presents the connection between these four methodology parts, the chapters they cover and the subquestions addressed in each section.

Sub-question 1 on giving the transport mode decision a social practice form, requires information on the social practice theory and the case. The background information on social practices is provided by analysing the state of the art through *literature research*, whereas the case implementation requires a *case study* and *conceptual framework*. Then, **sub-question 2** analyses the typical macro-behaviour of models with action adaption through social interaction as opposed to belief adaption. This macro-behaviour is retrieved from analysing related work through a *literature research*. Furthermore, with answering **sub-question 3**, challenges in evaluating models within the field of social and behavioural studies is addressed. This is done by *validating* the created models and describing the complications within this process, and by *analysing the sensitivity* of the model. Then, **sub-question 4** poses the question on how opinion dynamics resulting from action adaption differ from opinion dynamics resulting from belief adaption, which requires a *simulation study* to test the hypotheses on expected model outcomes retrieved from literature on transport mode choices and opinion dynamics. Subsequently, **sub question 5** requires insight in the impact of implementing restricted information-transparency by introducing theory of mind capabilities. For answering this sub-question, *simulation runs* are performed to compare results from both versions of the model. For **sub-question 6**, *model experiments* are required to test the effect of social capital on opinion dynamics.

The tool used for the agent-based model is NetLogo. As Gilbert (2008) states: "ABM is a computational method that enables a researcher to create, analyse, and experiment with models composed of agents that interact within an environment". Furthermore, NetLogo is a well known tool within the ABM-community, making the model accessible to a wide public (Tisue & Wilensky, 2004). For the analysis of data provided by simulation

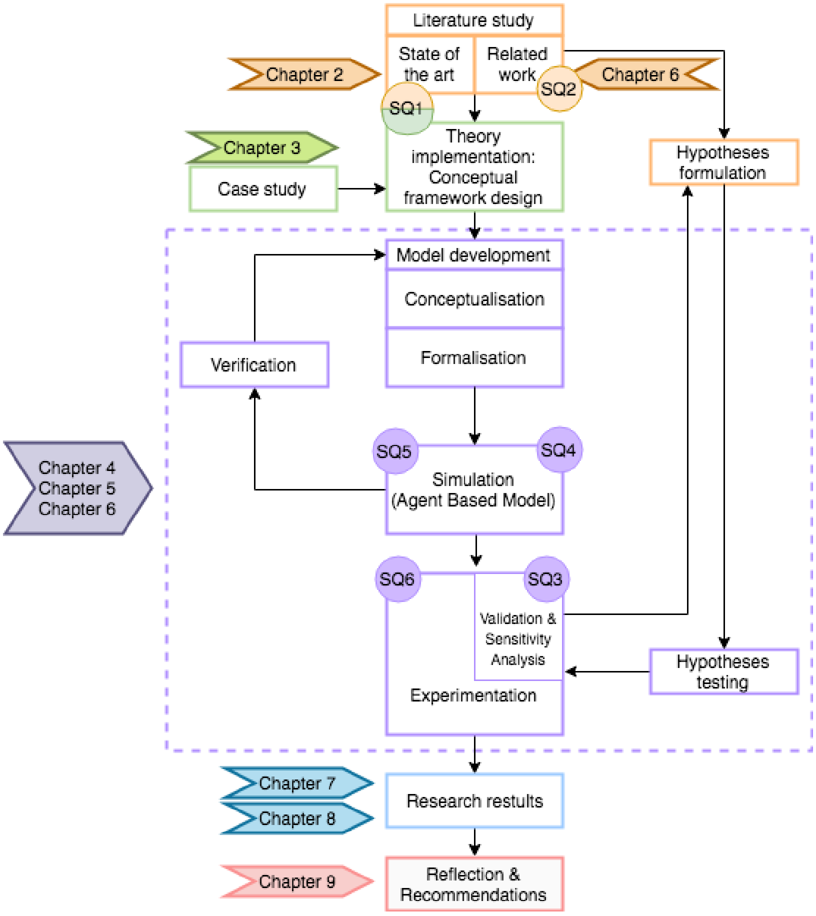

Figure 1.1: Overview of the methodology used within this thesis

runs, Python is used. Sensitivity Analysis is also executed within the Python environment by using the PyNetLogo interface as designed by (Jaxa-Rozen & Kwakkel, 2018a) (2018a). Specifications on versions and packages used within this study can be found in Appendix F.

1.5. RESEARCH STRUCTURE

Firstly, Chapter two of this research proposal describes the different concepts and theories that are at the core of this research. Subsequently, Chapter three will present the case study, the different components of the studied system, and lastly applies these components to the case study. In Chapter 4, the three models used within this study are presented and the model design of the two models created within this study is presented. Chapter 5 subsequently presented the verification, validation and sensitivity analysis of the created agent-based models. Then, chapter six firstly presents the related work resulting in hypotheses providing the means for comparing belief-adaption models to action-adaption models. The second section of this chapter provides results of model runs under fixed parameter settings and and compares the results to expected outcomes as presented in the hypotheses within this section. The third section of Chapter 6 lastly provides outcomes of model runs with parameters varied in light of analysing the influence of network connectivity on opinion dynamics for the different models. Subsequently, Chapter 7 provides a discussion on the model and found results. Hereafter, Chapter 8 summarises all findings of this study. Lastly, Chapter 9 describes the relevance of this research to society, science and the EPA masters programme, followed by a personal reflection.

Important is to note that this thesis can be read from two perspectives, i.e., from a multi-actor system perspective and from an agent-based perspective. The multi-actor system perspective focuses on platform development (i.e., to what extend this study contributes to improving the quality of simulated social agents). The agent-based perspective focuses on the empirical side of the research (thus the extend to which the model helps representing and understanding human behaviour). Both perspectives require different approaches, since other findings are relevant. However, since both perspectives are relevant for answering research questions, both approaches are incorporated in this thesis. Throughout the theses, findings that relate to one of these two perspectives instead of both are explicitly linked to these perspectives.

2

BACKGROUND LITERATURE

"There are in fact two things, science and opinion;
the former begets knowledge, the latter ignorance."

Hippocrates

In this chapter, the key concepts and theoretical frameworks this research rests upon are presented. The knowledge gaps, that have been briefly addressed in chapter 1.2, will be further explored through a literature study, and are presented in this chapter.

2.1. SOCIAL PRACTICE THEORY

Social practice theory is shaped over the last 40 years. Over this course of development, many researchers contributed to the subject, leading to many different versions of social practice theory. Amongst others, the main founders of the theory include Theodore Schatzki, Anthony Giddens and Pierre Bourdieu Kuijer (2014). Social practice theory focuses on 'practices'. Reckwitz 2002 gives the following definition of practices:

> “A practice is a routinised type of behaviour which consists of several elements, interconnected to one other: forms of bodily activities, forms of mental activities, ‘things’ and their use, a background knowledge in the form of understanding, know-how, states of emotion and motivational knowledge."

Schatzki (1996) describes practices as “a nexus of doings and sayings”. Examples of practices are ways of commuting, eating and studying.

Integrating the social practice theory into agent-based models is one of the many options for incorporating social motives to the analysis of decision-making processes of simulated actors (Mercuur, 2018). This theoretical framework is fitting since it provides a holistic perspective on evolving contexts and connected beliefs and values. (Hargreaves, 2011). This holistic approach partly lies in the positioning of the individual. Reckwitz (2002) described the role of the individual within practices and emphasises that individuals are solely the carriers of social practices and not the driving forces behind societal change as they are often positioned. It is this decentralisation of the individual that offers a very different view on the relationship between action and practitioner and thus behaviour Kuijer (2014). Furthermore, Shove & Pantzar (2007) state that social practices exist through the execution of actions they are based on and thus, arise and dissolve by occasions of these actions, triggered by carriers. Other than humans, (other) physical objects can be a carrier of practices as well as objects can interact with individuals when carrying out a practice (Reckwitz, 2002). Shove et al. (2012) acknowledge this collection of ever-changing interconnected elements, and describe social practices as an entity consisting of three elements: *material* (the physical facets), *competence* (skills and know-how needed to perform a practice) and *meaning* (the symbols, emotions and aspirations that are connected to a practice). For example, the practice of driving is a connection of the material car, the meaning of transport and the competence to drive it. The practice of driving then is connected to other practices, such as repairing, where they share the meaning of masculinity (figure 2.1). Besides sharing elements, social practices can also compete; such as the practice of commuting by train or by car. Both sharing and competing over elements can cause practices to co-evolve over time (Pooley et al., 2011).

With this focus on the doing rather than on the individual, social practice theory states that shaping human behaviour can be done more effectively through transforming a practice in the wanted direction than through trying to influence individuals (Balke et al., 2014). This way, social practices arise, progress and eventually dissolve as a result of the constant rearrangements between the practice elements and between those elements and the carrier (Balke et al., 2014). As Warde (2005) notes: "The principal implication of practice theory is that the sources of changed behaviour lie in the development of

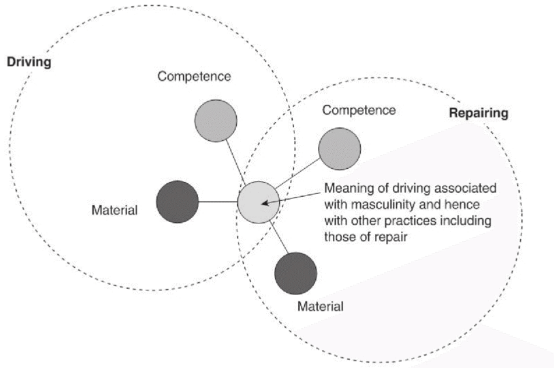

Figure 2.1: The interconnectedness of practices (Shove et al., 2012)

practices themselves". Then, the meaning associated with a certain practice can appeal in a different way to the individual's beliefs, which changes how and if an individual is a carrier of the practice. Hence, in the design of social practice agents, it is important that the social practice agents' decisions are based on the practices they carry.

Moreover, the social nature of social practices can be found in two theory-elements (Mercuur et al., 2018). Firstly, social practices can be executed by more than one person, leading to social interaction (Dignum et al., 2015). Some social practices even lose their purpose if they are not performed in pairs or groups, such as the practice of greeting. Secondly, social practices are social as they are similar for (a group of) people (Reckwitz, 2002). Social practices can be the foundation of social norms and play a guiding role in social interaction because of shared elements of social practices or shared beliefs on element-relations.

Enriching agents with these social characteristics would bring a contribution to the world of ABM, as many authors have addressed the critical lack of social skills of agents (Kaminka, 2013; Mercuur, Dignum & Kasima, 2017; Mercuur, Dignum & Jonker, 2018). Kaminka 2013 states that the common used approach of adding ad hoc communication and coordination skills creates superficial task-specific behaviour, which not always leads to correct social interaction. Kaminka 2013 lists component processes such as recognition, understanding and comparison as essential for social intelligence. Nonetheless, Kaminka's approach is reasoned from an individualistic perspective, whereas the social practice theory focuses on the idea that through engaging with practices, individuals come to a different level of understanding oneself and the world (Warde, 2005). This 'practical consciousness' does not imply passiveness, as in the social practice theory agents need to deliberately navigate through practice elements and make decisions and shape their beliefs accordingly (Warde, 2005; Balke et al., 2014). For example, prior to the practice 'rollerblading', one will negotiate with oneself whether the competences and materials are sufficient and if the meanings fit their beliefs. Subsequently, the negotiation moves outward and involves other agents that can make the practice possible or more enjoyable.

Lastly, Dignum, Jonker, Prada & Dignum (2014) emphasise the urge for developing general individual social intelligence building blocks, as this would not only increase the realism of models but also reduce the need for control and programming effort in decision-making simulations. However, at this point there is little knowledge on how all components of the social practice theory as described in this section can be integrated into agent-based models in order to form these building blocks. Therefore. this thesis will focus on the knowledge gaps concerning the steps needed for formalisation of social practice theory to an agent-based model.

2.2. THEORY OF MIND

In this research, the slow-thinking cognitive system of agents is addressed. This system entails the process when agents intentionally make a decision and thus explicitly form their preferences step-wise. It captures conscious decisions that require effort and attention and are not just an automatic repetition of past-made choices (i.e., habit-based fast-thinking decision-making) (Kahneman, 2011). Subsequently, a specific part of this slow-thinking systems is selected; the theory of mind (ToM). Between the ages of three to five, people start developing the ability to analyse situations from not only one's own perspective but also from the perspective of other people involved (Wellman et al., 2001). By doing this, the appraisal of other people's knowledge, desires, beliefs and intentions are formed, leading to a chance attribution to possible actions of others (Baron-Cohen et al., 1985). This is called 'theory of mind' (Baron-Cohen et al., 1985). The visualisation of other peoples mental state then serves as an input for one's own believes and choices. ToM is often associated with empathy and it is true that they partly influence the same constructs (Lawrence et al., 2004). Hence, when a person cannot predict the state of another person, the ability of having empathy is restricted. Although these concepts are intertwined, due to the difficulty that arises when the two need to be treated as different constructs, this study will only focus on ToM-capabilities.

Theory of mind is captured in this study since in the state of the art research concerning opinion dynamics, it is often assumed agents are capable to directly make a just observation and interpretation of others' opinion (Sun & Müller, 2013). However, this way the complexity of learning about others is reduced, as often there is no direct communication about opinions leading to imperfect interpretations of others' behaviour and opinion. This perception often does not correspond with somebody's actual beliefs. The degree to which one can make a just appraisal of others' beliefs is partly subject to the theory of mind capabilities of this person.

Figure 2.2 gives a conceptual overview of how the theory of mind is connected to other theoretical components within this study. The darker grey blocks represent theoretical elements included in this study, whereas the blocks in lighter grey represent theoretical components that are outside the scope of this research.

Two types of theory of mind can be distinguished: social-perceptual ToM, where a person forms expectations about another person through direct communication and social-cognitive ToM, where persons are not communicating directly but are still connected in such a way that they form expectations about each other (for example because they know that they have the same goal to reach). In this study, the latter form of ToM is used. However, the definition of the theory of mind needs to be sharpened. The term has been widely used in science, but due to different levels of description in different scientific fields where the term carries different connotations, the exact meaning of the theory of mind has become vague and sometimes even contrasting (Schaafsma et al.,

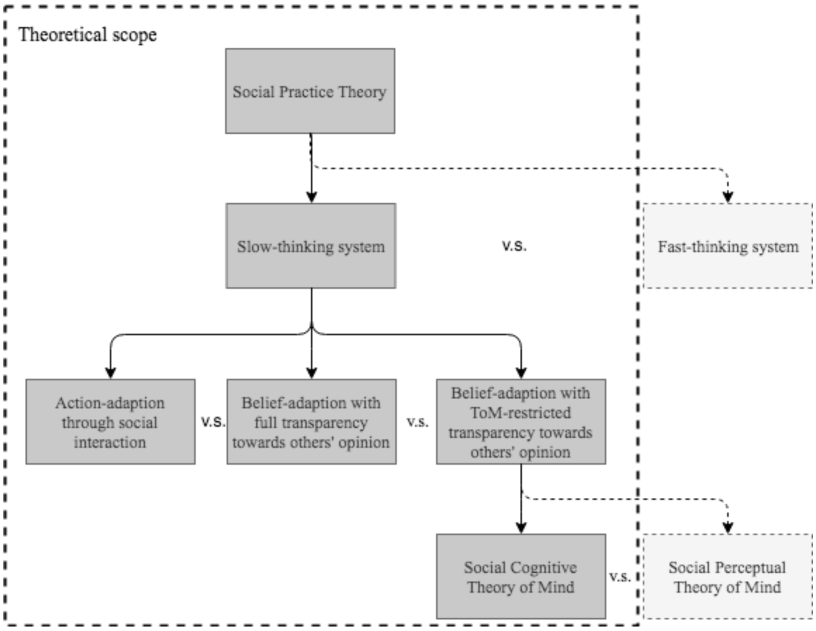

Figure 2.2: A conceptual overview of the theoretical scope

2015). Therefore, in this research a specific definition for the theory of mind is used, which is based on the literature of Leslie (2001) and Leslie et al. (2004):
The theory of mind is the mechanism that provides agents with beliefs about first-order mental states, (initial) social characteristics that influence group decision-making and a recursive learning cycle that is fuelled by belief-updates.

Three main concepts can be extracted from this definition. Firstly, first-order mental states can be seen as 'he/she thinks x' processes, whereas second-order mental states can be seen as 'he/she thinks that he/she thinks x'. Furthermore, according to Leslie et al. (2004), three mental states play a leading part in our common-sense interpretations: (i) beliefs; how the state of the world appears to be for an agent, (ii) desires; the building blocks for goals of an agent and (iii) pretence; the discrepancy between what people do and say. Lastly, the social characteristics that influence group decision-making that is referred to in the definition are traits that influence:

- The extent to which one takes mental states of others into account and lets this information influence one's own decision-making process.

- The extent to which one learns and hereby updates believes of oneself and decision-making associates.

Examples of these characteristics are empathy and confidence in one's own predictions.

How the theory of mind can be captured in an ABM concerning in a cooperative scenario not yet known. Therefore, this is one of the main focus points of this thesis. To fill this knowledge gap, analysis is performed on how to capture agents' personal(ity) characteristics, their estimations on the personal(ity) characteristics of others and the processing of this information through learning in a quatitative manner.

2.3. OPINION DYNAMICS

Our daily lives, and even society in general, depends on the beliefs we hold and opinions we form. Therefore, beliefs of individuals are highly important for how their daily life is shaped and how they subsequently shape society (Yu et al., 2016). Opinion formation is all about personal and social learning. Opinion dynamics then can be seen as an attempt to understand how these social learning processes through interactions on micro-level, can result in macro-level shifts in opinions (Yu et al., 2016). A distinction can be made between different opinion dynamics models, among others the following are well-known within the field of opinion dynamics; the voter model (e.g.: Sood & Redner (2005)), the Sznajd model (e.g.: Sznajd-Weron (2005)), the contagion model (e.g.: Pacheco (2012)) and the social influence model (e.g.: Flache et al. (2017)). As these models all focus on different aspects of opinion dynamics, the social influence model is chosen to be the benchmark of opinion dynamics within this study. This model is chosen as the benchmark, as social interaction is one of the main topics within this study. Acemoglu & Ozdaglar (2011) divide opinion formation in its social influence form into three components:

1. **Priors.** There has to be a starting point for opinion development. Individuals have prior views about subjects before they encounter other viewpoints. These prior views can be a result of many aspects, under which demographic factors, culture, past events and social networks. Priors are of a certain strength, meaning that view points might be diffuse or deeply ingrained, leading to varying degrees of openness to dissimilar beliefs. For social interaction models, these priors most often hold continuous values (Deffuant et al., 2000).

2. **Sources of information.** The information received by individuals form the basis of the evolution of their opinions. Information can flow from personal experiences, observing and appraising others, direct communication with others and lastly from media sources. The sources of information can thus be influenced by an individual's social network, whereby individuals do not care equally about the opinion of others. A hierarchy is present within the influence of opinions, where strong relations have more influence on opinion-formation (e.g., family members, friends, colleagues).

3. **Method of information processing.** How are individuals' priors and new information obtained compressed into new beliefs? A Bayesian- or non-Bayesian approach can be used to address this question. The Bayesian leaning approach theorises that given the state of the world, individuals optimally update their beliefs. This approach requires agents to connect a certain probability to states of other agents as a result of the signs this agent gives and as a result of the probability of this state in the physical context at that moment. For example; when one needs to categorise a relatively shy person as a mathematics PhD student or a business student, one might assume this person would rather be a math PhD student than a business student. However, there are far less mathematics PhD students than business students, so the probability of the person being a business student is larger, despite the shy character. These probabilities are translated into the Bayesian rule,

which then provides the 'best' mathematical estimation of relevant unknowns. On the other hand there are Non-Bayesian models, which refer to all models without the described approach. Some of the aggregations of priors and retrieved information will be done similarly as compared to the Bayesian approach, meaning agents will form a mathematical estimate of the unknowns given their priors and understanding of their physical context. However, other information processing will not use Bayesian rule and thus will follow a simpler adaption of beliefs, which Acemoglu & Ozdaglar (2011) describe as similar to being 'infected' by a disease.

Figure 2.3 summarises the described opinion formation components. How these components are translated into this study, will be described in chapter 4.

Figure 2.3: Overview of opinion formation components

As the the concept of 'beliefs' is often used in combination with the concept of opinions, it is necessary to define what is understood as an opinion and respectively as belief. Beliefs embody how the state of the world appears to be for an agent. Opinions are the consolidation of an individuals beliefs about to what degree a subject is connected to a specific value, and the importance attached to this value. In example, an individual has the belief that the car is connected to the value of environmental friendliness, but in a negative manner. This same individual attaches high importance to this value of environmental friendliness. These to ingredients can result in the opinion "The car is a threat for today's society". When the same belief was accompanied by a low importance given to environmental friendliness, a completely different opinion could arise, such as "Although driving can cause harm to the environment, there are more important issues to be concerned about".
Outside of the transport domain, beliefs are more frequently used as a standard for social adaption, for example as described by Nowak et al. (1990) in their theory of social impact. This study will analyse the effects in the opinion dynamics, when comparison and adjustments based on actions are changed into comparisons and updates of beliefs.

2.4. SOCIAL INFLUENCE

Social influence is an inescapable component of social interaction. Through social interaction, individuals often adjust their personal opinions, beliefs or behaviour (Flache et al., 2017). This influence can arise from different internal processes; individuals might be persuaded by others (Myers, 1982), or they might follow the footsteps of others due to social pressure to behave according social norms (Akers et al., 1995; Bikhchandani et al., 1992; Festinger et al., 1950). The social interaction then can form dynamics that result in emergent behaviour, where the outcome of individual interactions can be unexpected when zooming in on individuals personal beliefs (Flache et al., 2017). Despite the importance of social interaction, the exact process of social influence remains mystifying, as there is much uncertainty about the underlying mechanisms and conditions (Flache et al., 2017). Because of the fact that ABM literature cannot provide explanations for social influence dynamics (Flache et al., 2017), in this study we will focus on one of the classes of social influence models. Three typical classes of social influence models can be distinguished:

- **Models with similarity biased influence.** Individuals adjust their opinions in order to reduce opinion differences with other individuals that they find to be similar to themselves. How much similarity is needed for individuals to partly align their opinions depends on psychological systems such as social identity and trust (Flache et al., 2017).
- **Models of assimilative social influence.** Individuals that are connected by a structural relationship always exert influence each other (Flache et al., 2017). For example, individuals that are part of the same community will have an influence relationship.
- **Models with repulsive influence.** Individuals that are sufficiently different are attracted to each other by influencing each others' opinion formation. Just like similarity biased influence, psychological systems (e.g. "ego-involvement") play a role in where the threshold for enough dissimilarity lies for this model to be triggered (Flache et al., 2017).

In this research, the model of similarity biased influence is used to model social influence. Similarity biased influence is suitable for this study as it is frequently used and substantiated in studies on opinion formation (Moschis, 1976; Teşileanu & Meyer-Ortmanns, 2006). For example, Jones & Gerard (1967) state that individuals use reference groups in social comparison situations, which are more likely to consist of other individuals who are "at the same level" instead of individuals that excel or fall behind in specific aspects compared to oneself. Jones & Gerard (1967) describe this referent as the "co-oriented peer", which shows parable value perspectives. A practical example comes from Vazquez et al. (2003), through analysing politics-related opinion formation. In this model, rightist and leftist interact and compare themselves to centrist, but do not interact directly with each other, as they find themselves too dissimilar (Vazquez et al., 2003).

When interpersonal comparisons are made, a reference point is required. This reference point can be based on observable characteristics that are explicitly expressed or shown, or on characteristics that are not directly expressed by other agents. The first possibility is also called the 'public characteristics' and the latter is also known as 'private characteristics' (Tang et al., 2019). In this study, public characteristics can be seen as actions taken by agents, and private characteristics can be seen as agents' beliefs and values. The latter has been chosen as a reference point within this study.

3

EXPLORATION OF THE SYSTEM IN LIGHT OF SOCIAL PRACTICE THEORY

In this chapter, the system captured by the in chapter 2 described theoretical framework is described. Through the description of the system, an answer to sub question 1: *How can transport mode decision-making be shaped as a social practice?*, is presented. First, the case that is been used to put the SoPrA system into context is presented. Subsequently, the SoPrA system itself as designed by Mercuur et al. (2018) is presented. After this, an addition to the SoPrA system is proposed. Lastly, the SoPrA system is applied to the case study.

3

3.1. THE CASE

A case study will be used for the analysis performed within this thesis. A case study is used, since the context determines the nature of a social practice. As an illustration of this context-dependency; the social practice of fishing, addresses different political and ecological influences in different physical environments, and thus describes different social practice-elements in different areas (Jüttner, 2017). Therefore, this study will be conducted for a specific transport-scenario.

The transport field embodies a tremendous amount of policies for the (attempt) regulation of transport mode choices and vehicle movements (Natalini & Bravo, 2014). Many transport studies analyse commuting from a rational choice framework, where commuters make a choice for their mode of transport based on certain criteria such as costs and time (Guell et al., 2012). For the case study used in this research, individuals will also make a choice regarding their mode of transport, but the focus is shifted from rational criteria towards social constructs underlying this decision. Pettifor et al. 2017 found that social influence does steer vehicle choices. Because of this and the fact that different modes can be connected to values through agent beliefs, this domain has been found appropriate to serve as a case. Because of the focus on social influences, the case will involve a group of twenty agents. The case used for this study is as follows: *Twenty initially ill-acquainted students leave their university faculty to head to the location for a compulsory seminar, for which car, public transport and bicycle are possible travel-modes.*

3.2. SYSTEM IDENTIFICATION AND DECOMPOSITION

This chapter describes the system components and -boundaries. The system consists of practices, agents, the environment and relations between these components. This chapter describes what is and is not understood as the described system components. This will be structured by key concepts as defined by Mercuur et al. (2018) in their UML of social practice agents (SoPrA) (figure 3.1), followed by two new components to be added.

3.2.1. THE SOPRA SYSTEM

Mercuur et al. (2018) designed a computational model in the Unified Modelling Language (UML) of social practice agents (SoPrA), which shows the different components that social practices consist of, and the relation between these components. As can be seen in the UML (figure 3.1), social practices consist of activities, the corresponding elements (i.e., material and meaning), and the relation agents have towards these activities, their elements and other agents. The meaning and material elements of social practices are respectively represented in the UML by values and context elements. The relation of agents to other agents is embodied by the context-element component, more specifically; the social context of agents.

This paragraph gives a description these components and their connections. Habitual triggers will not be discussed, as with the focus on intentional decision-making this is not within the scope of this research.

First of all, **social practices** are represented by the UML in its entirety. Moreover, all concepts displayed in the UML of figure 3.1, can be seen as ingredients for the social practice performance. Summarising, practices are built from their elements (i.e., ma-

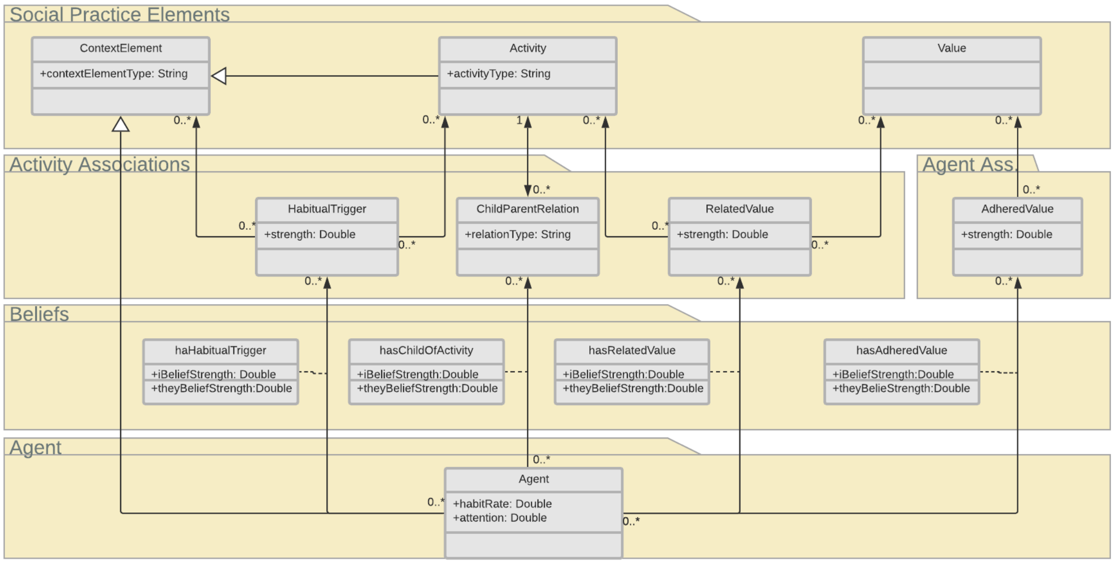

Figure 3.1: Overview of SoPrA in UML

terial and meaning components in this UML), from activities that represent the bodily movement and from the relation between these elements that agents (as carriers of activities) belief in. The system in the UML can describe the internal behaviour of social practices, but social practices are also connected to each other, as described in Chapter 2. This interconnectedness allows social practices to co-evolve. However, in this study, we will not include the evolution of social practices. The elements of practices are held constant in this study, as these dynamics are believed to only be present in long-term simulations, whereas this study has a time scope of a couple of weeks, as it concerns intentional decision-making, which will turn into habitual behaviour with a long time-horizon. Thus, within this study the static aspects of social practice theory are analysed.

Furthermore, **activities** are an important component of the social practice system. Activities are all bodily movements that allow social practices to be executed (Mercuur et al., 2018). Activities are built from different actions that follow from an active goal-state, which are fulfilled in order to retrieve a certain reward (Metzinger & Gallese, 2003). For example, the activity of driving consists of actions such as steering the wheel, switching gears, accelerating and braking. Awareness about activities allow agents to form associations between activities and their elements, context-elements and beliefs, which result in first- and second order perspectives (Metzinger & Gallese, 2003).

Also, as carriers of the social practices, **agents** fulfil an important role in the social practice system. In this study, agents will be the autonomous instances that follow rules presented by the social practices they are implementing and behave accordingly (Narasimhan et al., n.d.). The rules embodied by social practices partly arise from the practice-elements (i.e., meaning, material and competence). Activities all come with their own related elements, but an agent also has individual adhered values, competences, affordances and beliefs. In other words, agents attach different strengths to values to conceptualise their ideals. The difference in importance attributed to an element characteristic will lead to personal desires. However, these desires will not directly be decisive for the action to be chosen, two other aspects also influence the preferences of an agent.

One aspect that gives direction to the decision-making process besides agent's values, are personal and shared beliefs. For example, an agent might attribute high importance to the value 'environmental friendliness', but surprisingly might still choose to travel by car when the agent beliefs this is an environmental friendly manner of transport. Besides personal beliefs, agents also have social beliefs. Social beliefs concern the shared strengths an agent has with other agents regarding their beliefs. An agent has beliefs on how other agents' their association-relations for specific actions look, and if this is similar to their own association-relations. The sharedness of these beliefs and their associated social practice changes over time. Social dynamics and frequency have an influence on which beliefs and views are omnipresent, and which beliefs disappear to the background (Mercuur et al., 2018). Furthermore, the level of sharedness is also practice-specific, as some practices require more reasoning about shared beliefs than other practices. For example, driving during rush hour requires more anticipation on what other might think and do then walking through the woods. This paper studies the dynamics of shared beliefs and practices, as a result of social interaction.

Furthermore, preferences of agents can be influenced by what they think the preferences of other agents are, which in one model-version will be shaped by agents' theory of mind (ToM) capacity. This slightly overlaps with having shared beliefs, as the extend to which agents can have shared beliefs depends on the capacity of 'reading minds'. However, ToM capabilities are more than this, as they are not only connected to agent beliefs, but also to others' values and they can help predict the willingness of agents to adjust their plans to others, i.e. to cooperate. Only first-order theory of mind is considered in this study. This means, agents reason about the possible preferences of other agents, but do not take into account that those other agents might also adjust their preferences according to their believed preferences of agents in the group. Furthermore, the level of ToM capability is influenced by agent's personality. However, this will not be incorporated in this model. The correlation between ToM capabilities and agent's values and beliefs concerning transport modes is not known and left out of scope for this thesis. Although agents will be given a random capacity for ToM, to keep a consistent internal system for the agent, the correlation between this and an agents prosociality has been analysed by Declerck & Bogaert (2008) and is taken into account in the study. Being prosocial means to be a natural cooperator, striving for maximum joint positive outcomes and aiming to solve disagreements (Declerck & Bogaert, 2008). The more and agent interacts with a specific other agent, the more input can be gathered about the beliefs of this other agent.

Then, after a decision for a specific travel mode has been made, agents will evaluate their choice. Through this evaluation, agents have the capability to link a certain reward-level to their choice, and based on this learn from their past behaviour. These lessons learned can then be used as input for future decisions. Besides lessons learned, the stress- and enjoyment-level experiences from the transport mode is taken into account and so is social comparison.

The next important element for guiding agents in their social practice implementation are **values**. As mentioned in the previous paragraph, each social practice has its own practice-specific collection of values, but each agent attributes their own weight to these values. Action-related values are activated in agents when they become relevant in the context and the agent attributed significant weight to them (Schwartz, 2012). The strength of an agent's individual values is a predictor for it's intentions and internal drives that affect behaviour (Mercuur, 2015; Dignum et al., 2015). This way, values represent goals to be perceived, resulting in the need for agents to satisfy their held values in proportion to the attributed importance to the value (Mercuur, 2015). Because this satisfaction of values can be attained by the implementation of certain actions, values facilitate agents to form their personal view on social practices. In this study, values are taken as to be the meaning-element of social practices. Values prove to be a good concept to represent the meaning-element as they are teleological, shared, can serve as decision-making criteria and can be ordered by importance (Mercuur et al., 2018; Schwartz, 2012). Firstly, values are teleological because they present the end to a purpose as they refer to desirable goals (Mercuur et al., 2018; Schwartz, 2012). Secondly, values are shared, as values are widely understood concepts (Schwartz et al., 2012). This allows agents to compare different situations with each other, with respect to a certain value (Cranefield et al., 2017). This way, values become an instrument to measure the effect of activities in certain scenarios (Cranefield et al., 2017). Thirdly, values can be used as criteria to guide the decision-making process and its evaluation (Schwartz, 2012). Lastly, internally ordering of values can support this decision-making. This ordering is performed by two mechanisms: by Schwartz' (2012) intrinsic opposition model and by personal preference (Cranefield et al., 2017). Through personal preference, values are given a relative importance, such that when evaluating a decision where conflicting values are involved, the alternative that satisfy the most important value is preferred (Cranefield et al., 2017). The trade-off an agent makes between different values is one of the guiding elements in agent behaviour (Schwartz, 1994). Values are deeply manifested in the internal system of individuals. Although people's values can change over time, most of the time an external trigger is necessary for this to occur (Rokeach, 2008). Because of this reason, agents' values remain unaffected within this study. Values influence the decision the most when they are prioritised by agents and relevant in the context (Schwartz, 2012). This hierarchical characteristic makes values differ from norms and attitudes (Schwartz, 2012). Norms and long-term goals also influence decision-making, but because they are often a result of the value system (Cranefield et al., 2017), they are kept out of scope in this study.

The last important component of the SoPrA system as it is designed by (Mercuur et al., 2018), are **context elements**. Context elements form decision-making environment, which concerns both the physical and the social context. It is the aim of social practices to integrate agents with their surrounding environment, and let agents determine how this context relates to their experiences and capabilities (Dignum et al., 2015). Furthermore, the characterisation of social practice elements is subjected to physical contextual boundaries, i.e. the time and space of the practice. For example, the practice of driving is different in the USA than in The Netherlands and also different now than it was in the early 1900's. For this study, physical context elements are considered given and do not change over time. Thus, for all transport mode choices, car, bus and bike are available, including their infrastructure. It depends on the agent if they have the necessary affordances to accompany these transport modes. The weather will be included as a context-element, as it is directly connected to the values regarding comfort. On a social note, a social context can accentuate certain personal values. For example, interaction with someone that is strongly committed to the environment could influence the travel mode options you propose for travelling together. In short, all aspects of an agent's external world that can influence decision-making are believed to be context elements.

3.2.2. AN ADDITION TO THE SOPRA SYSTEM

In order to connect the SoPrA system to this study, three adjustments have been made; competences and affordances have been added as social practice elements and a simplification has been made regarding agent beliefs.

Firstly, social practices are connected to **competences** that are required to successfully execute the practice. For this case, competences are the knowledge on how to drive a car, how to navigate through traffic when driving a vehicle and determining when public transport departs (Cass & Faulconbridge, 2016). Competences (together with affordances, paragraph X.6) provide the first restriction to which social practices are possible for an agent. For example, when an agent does not know how to drive a car, it is not a possibility for the agent to drive the car to the seminar. Nonetheless, competences of other agents can compensate for the lack of this competence of the agent; e.g. when a classmate does have a drivers licence and is willing to carpool. Agent's competences will not change over time, because their evolvement is not a result of social interaction, leading to this dynamic to be out of scope of this study.

The second added component is **affordances**. Gibson (1977) refers to affordances as 'the complementary of the animal and the environment'. Moreover, affordances are context-elements that offer the agent certain action-possibility. For example, the availability or presence of a bicycle provides the possibility of riding the bicycle. However, having a bicycle in the direct environment does not mean choosing the bicycle is the obvious answer to the transport mode choice dilemma, it only allows you to implement this option when desired. In short, affordances are the context-elements required for a certain activity (Mercuur, 2018b).

Lastly, a simplification regarding **beliefs** has been made. In the study of Mercuur et al. (2018), it is considered that individuals have beliefs about all elements of a social practice. However, only beliefs about a value-transport mode relation are considered in this study. This means that the beliefs on a relation between competences and affordances and transport modes are the same for everyone. For example, all agents belief that there is a relation between driving and having to own a drivers license, and between biking and having to own a bike. Then, through social influence agents can influence each others *beliefs*, resulting in a shifting *opinion*. In other words, opinions are re-shaped due to evolving beliefs while values remain constant.

3.3. SoPrA SYSTEM APPLIED TO THE CASE STUDY

In order to contribute to answering the research questions of this study, it is necessary to see how the SoPrA components can be used to describe the transport mode choice case. When applying the SoPrA system to the case study, specific design requirements arise. These design-requirements are presented in this section and are indicated by the component name followed by the design requirement number within the component list.

Social practice

- **SP1:** Social practices and social interaction influence each other through a causal loop, causing both to evolve over time. Social practices influence rules for social interaction and social interaction influences the characteristics of a social practice (Mercuur, 2018). In this study, only the influence of social practices on social interaction are taken into account.

Agents

- **A1:** A first requirement for simulating social processes is the presence of social agents. Social agents are believed to be agents which can reason about other agents' perception and preference and take this information into account when forming their own preference (Goldspink et al., 2002). Thus, through social awareness, agents are capable of influencing one another (Macy & Willer, 2002). This allows agents' beliefs on how values and transport modes are connected to adapt over time.
- **A2:** Agents can extract information from the current social and physical context elements and form or adjust their preferences accordingly (Dignum et al., 2015). For the social environment, this concerns the relation strength between agents. For the physical environment, this concerns the presence of affordances, as presented in table 3.1 which regulates the transport mode-options.
- **A3:** Agents can have a perception on the beliefs, values and transport satisfaction of other agents, i.e.; a theory of mind.
- **A4:** Agents have a certain level of prosociality, which partly determined the extend to which an agent is willing to take others' beliefs into account. This prosociality leven is connected to their ToM (Declerck & Bogaert, 2008).
- **A5:** The extend to which an agent adapts its beliefs to the beliefs of another agent, depends on the prosocialness of an agent, the prosocialness of the other agent, their similarity and their current relation strength (Sobel et al., 2005;DeAngelo & McCannon, 2017).
- **A6:** Agents can evaluate the implemented activity and by doing this can obtain a certain transport satisfaction level (Dignum & Dignum, 2015; Macy & Willer, 2002; Mercuur et al., 2018). This transport satisfaction level is build up from agent's travel stress, -enjoyment, social comparison and intrapersonal comparison (Abou-Zeid & Ben-Akiva, 2011).

Beliefs

- **B1:** An agent's beliefs can adapt over time due to the comparison of beliefs during social interaction and though the satisfaction experience from previously belief-based choices (Mercuur, 2015). Thus, there is a social- and personal evaluation process leading to belief adaption.

Context

- **C1:** Social and physical context elements give direction to the way agents interact and influence each other (Narasimhan et al., n.d.). In this study, agents all have the same beliefs towards physical context elements (i.e., affordances). For example; agents think one needs a drivers license and a car in order to implement the activity "Drive to lecture", leading to a situation that when both components are present and the values and beliefs of agents steer into the direction of this activity, they will both prefer the car as a mode of transport. Concerning the social environment, the social network of agents consists of their reference group of co-oriented peers and their relationship with those agents. The number of agents within this reference group and the strength of the relation with these co-oriented peers determines the extend to which an agent can adapt its beliefs.

Competences

- **Cp1:**Activities require competences which implies that without this competence, agents become dependent on others when wanting to choose this option.

Affordances

- **Af1:** Affordances connected to an activity need to be available in order for an agent to be able to implement the activity (Gibson, 1979). Just as with competences, if agents do not have access to required affordances of their preferred activity themselves, they might try to join others that do have access to this affordance (e.g., through carpooling).

An overview of the specific affordances and competences that are required by the activities in this case study, is presented in table 3.1.

Activity	Affordances	Competences
Bike to seminar	Bicycle, cycle paths; rain gear; safety equipment	Cycling proficiency
Drive to seminars	Car; roads	Drivers license; navigation
Take bus to seminar	Bus; roads; bus stop; rain gear	Reading bus schedule; public transport card

Table 3.1: Transport-activity elements

3.4. CHAPTER SUMMARY

The aim of this chapter is to present travel mode choices as a social practice. The competences, affordances and values (representing social practice meanings) required by all transport modes are presented. Agents need to acquire these practice elements in order to have this transport mode as an option. This way, agents behaviour is shaped by their 'practical consciousness'.

4

MODEL DESIGN

This chapter describes the three models central in this study. Firstly, a description of each of these three models is presented. The models consist of two variants of belief adaption model specially created for this thesis and one model where agents adapt each others actions. The latter is not one specific model, but a qualitative model of statements made and results generated from related work. In section 4.2, the concept conceptualisation of the models designed for this study is discussed, followed by the formalisation of these concepts (section 4.3). By formulating the rules that govern the social interactions leading to evolving opinions and behaviour shifts in a computer simulation, the consequences of these rules can eventually be observed.

4.1. THE THREE MODELS

This study revolves around three types of models; two models where agents compare their beliefs to others and adjust their beliefs according to their findings and one model where agents compare their actions to the actions of others and adjust their actions accordingly. The two types of belief adaption models include one model where agents make decisions under full information transparency when it comes to the beliefs, values and satisfaction level of others. The other variant of the belief adaption model introduces restricted information transparency on others' beliefs, values and satisfaction through theory of mind capabilities. This section will describe the three models in more detail.

4.1.1. BELIEF ADAPTION MODEL UNDER FULL INFORMATION TRANSPARENCY

In the belief adaption model under full information transparency, social influence is exercised by agents that have full insights into other agents private characteristics. Agent preferences for a transport mode result from their beliefs and values. Agent beliefs can be influenced by others, but their values remain constant over time. Values are ought not to change during the simulation time, as values can be seen as the most deeply rooted private characteristic of agents. Hofstede 2001 includes values in his onion model (figure 4.1) as the core of our being, forming the basis of our practices. Hofstede describes values as a set of dilemmas that individuals need to consider when interacting with the world (Hofstede, 2001). Moreover, the more to the centre of Hofstede's onion model, the more deeply embedded the cultural component. Despite the fact that Hofstede's onion model describes the dynamics of cultures, the model can be applied to the system of this study. Within this study, values form the basis of practices. Agents first consider seven values as a set of dilemmas, that they ought to satisfy through their decision (i.e.: fun, comfort, relaxation, safety, environmental friendliness, efficiency and flexibility). The higher the importance attained to a value, the more often an agent will elaborate on transport mode options with the aim to satisfy this value. Each transport mode has a different ability to satisfy this value, depending on the agent's beliefs on this relation between value and transport mode. Thus, just as with Hofstede's onion model, values form the basis of the practice.

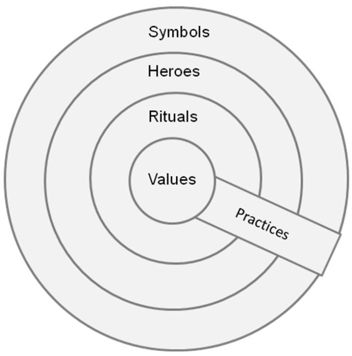

Figure 4.1: Hofstede's onion model (Hofstede, 2001)

Furthermore, in the field of transport, social influence often translates to comparison and adaption on the level of output behaviour. In this model however, the focus is not put on adapting actions, but on the comparison and adaption of agent beliefs. Furthermore, agents have insight to others' precise private characteristics, i.e.: beliefs, values and travel satisfaction. Agents use this information for the processes of (1) deciding who they find similar to themselves, (2) to adapt their beliefs and (3) to determine their intrapersonal travel satisfaction. This first process of determining who are included in the reference group of co-oriented peers, is done on the basis of value comparison (Jones & Gerard, 1967; Moschis, 1976). In other words; values form the prior comparison standard for agents within this model and thus with dissimilar values agents will not come to the stage of comparing or adapting their beliefs. Whether individuals consider themselves to be similar enough to establish a relation, is determined by a similarity threshold. Putting a threshold to individuals finding themselves similar, is introduced by the Deffuant-Weisbuch model (Weisbuch et al., 2002), a form of the bounded confidence model. The similarity is considered as a form of confidence between agents, and a direct indicator of the chance of interaction and the establishment of a relation between agents (Urena et al., 2018). Other than value similarity, the degree to which agents influence each other through their social connection depends on their prosocialness. Prosocial agents attract each other, whereas less prosocial agents prefer not to depend on others and hold on to their own beliefs. Together with the experienced travel satisfaction, this social interaction shapes the beliefs of agents and hereby determines their transport mode preference. In short, the model presents agents travelling from their university faculty to a compulsory seminar, and along the way their choices are affected by adapting beliefs through social interaction with their co-oriented peers.

4.1.2. BELIEF ADAPTION MODEL UNDER TOM-RESTRICTED INFORMATION TRANSPARENCY

This model is similar to the previous discussed modes exept for one aspect: instead of full insights in the private characteristics of others, in this model it is assumed that agent cannot have perfect information on others' private characteristics and thus are able to make misjudgements. This is done by providing agents with a theory of mind capacity, which determines their capability in determining others' private characteristics. Within the model, agents are differently skilled in making these estimations. Furthermore, some agents are not willing to put effort in estimating others private characteristics, as they are not interested in travelling together. The latter depends on one's prosocialness, and is based on a study performed by Declerck & Bogaert (2008). The more prosocial an agent is, the better their theory of mind capabilities.

Through theory of mind capabilities, the accuracy of an estimation on other agents (1) values, (2) beliefs and (3) travel satisfaction is determined. This implies, that the theory of mind capacity affect which other agents they see as to be their co-oriented peers, the direction of belief adaption through social influence and their own travel satisfaction as a result of intrapersonal comparison.

A conceptual framework resulting from the description of the two models designed for this study are presented in figure 4.2. The elements adjusted for the theory of mind included model are highlighted in blue.

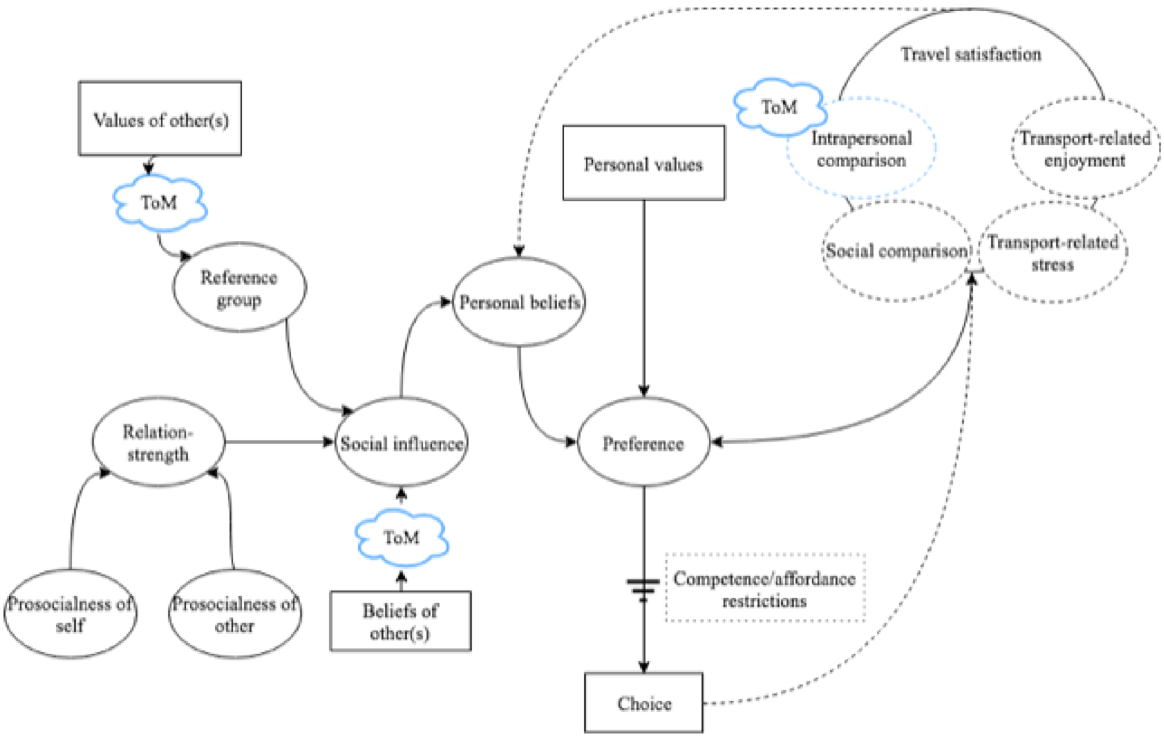

Figure 4.2: Extended conceptual framework of social influence based on agent beliefs

4.1.3. ACTION ADAPTATION MODELS

In many social systems, interpersonal dependency is described to rely on observations that lead to the adaption of behaviour (Moussaïd et al., 2013). Studies describe that through social interaction behaviour is adjusted (Macy et al., 2003). Also in the field of transport, the inclusion of social interaction is not a new phenomenon (Gitelson & Kerstetter, 1995). However, in these analyses of the influence of social interaction on choices concerning transport, agents often influence each other on the level of their behaviour. Hereby, behaviour is understood as the level where decisions are made, and thus all motions and signals visible for the outside world (Ettema et al., 2011). As for this study the only relevant signal for the outside world are transport mode choices. Therefore, 'behaviour' is specified to 'actions' within this study.

An example of such a study is conducted by Páez & Scott (2007). In this study, individuals reflect on the frequency by which alternatives are chosen, and by whom. Through this reflection, individuals mirror actions of other individuals in the system, as a function of their place in the social network. Also Carrasco & Miller (2009) search for the link between social interaction and travel behaviour, where agent's beliefs are similarly left out of scope. By using transport mode choices as the to be evaluated output and comparison standard, agents modify their behaviour to others. Thus, in this case the input of social evaluation are actions and the affected output of agents is also their actions.

A side note needs to be made concerning the fact that not all models studying transport mode choices focus on adapting actions. Nonetheless, the models that do shift away from this principle frequently focus on influence of (social) norms on transport mode choices instead of beliefs. This is often applied to cases where acquaintances influence each others transport mode choices through inter- or intrahousehold social interaction. Thus, through interactions within of between small, well-acquainted groups (for example Kroesen (2015) and Goetzke et al. (2015)). In this study, the focus is put on initially ill-acquainted individuals, that are not connected via a certain construct such as a household or group of friends, but find each other through the network en build a relationships over the simulation run.

4.2. CONCEPT FORMALISATION

The described components and system boundaries from Chapter 3 are formalised for the model within this section. Note that for this study, only the belief-oriented models are created for this research, whereas the action-oriented model is a qualitative sythesis of previously executed research. Therefore, only the belief-oriented models are subject of the concept formalisation in this section.

Through concept formalisation, context-dependent concepts can be read by the computer without facing ambiguity. The concept formalisation will be done by converting the concepts into a computer understandable analogue (Van Dam et al., 2012). This section is structured by firstly applying the three components of opinion formation as described in chapter 2.4 to the case study. Subsequently, the concept formalisation for the full information transparency is presented, followed by the concept formalisation for the ToM-restricting model. Within this concept formalisation, firstly the global variables are presented followed by the agent variables, both with their corresponding software data structure. Only essential variables are mentioned, i.e., intermediate variables solely required for the generation of other variables are excluded. Furthermore, additional explanation that is required for some of the variables can be found in appendix A. This is indicated by a **[number]**, which refers to the corresponding number in the list of assumptions and default parameter settings of appendix A.

4.2.1. BELIEF ADAPTION MODEL UNDER FULL INFORMATION TRANSPARENCY

This section provides the concept formalisation for the model with full information transparency.

APPLICATION OF THE THREE COMPONENTS OF OPINION FORMATION

The three components of opinion formation as described by Acemoglu & Ozdaglar (2011) and presented in chapter 2.4, can be applied to the case study. Within the case study, **priors** are determined by the travel type a student embodies, i.e.: the careful solo traveller, the status-oriented bon vivant, the pragmatic mover, the independent idealist and the uninhabited road user (see appendix C for more information). Because priors are represented by values in this study, priors are deeply embedded within agents and does not change over time. The travel type of a student provides an importance of 1, 2 or 3 points towards a value, which is translated to a random continuous number on the scale from 0 to 10 that corresponds with this importance (with 0 corresponding to not important, 10 corresponding to very important). Furthermore, the **sources of information** agents use in this study are personal experiences and the estimation of private characteristics of others. Lastly, a non-bayesian approach has been used for the **method of informa-**

tion processing. This choice has been made because the requirements that follow from the Bayesian rule are quite demanding and challenging and there can even be questioned if individuals could in reality handle such large information-sets in the limited time they have and take when making a decision and forming an opinion (Acemoglu & Ozdaglar, 2011). Another reason for this choice lies within the existence and availability of data needed for mathematical requirements of Bayes rule (Allahverdyan & Galstyan, 2014). Lastly, different studies found empirical evidence suggesting that the Bayesian approach is not a correct representation of human behaviour (Allahverdyan & Galstyan, 2014). Figure 4.3 displays the components of opinion formation in the light of this study.

Figure 4.3: Opinion formation components in the light of this study

GLOBAL VARIABLES

The global variables of the system are described with a reference to the respective initial parameter setting as assumptions necessary to incorporate these objects into the model.

Activities have (object): list **[22]**

- Required competence(s) (list) **[1]**
- Required affordance(s) (list) **[1]**
- Connected values (list) **[2]**

Area specific parameters: (int)

- Share of students with specific competences (% int >= 0) **[3]**
- Share of students with specific affordances (% int >= 0) **[3]**

Global agent variable:

- Similarity threshold (int >= 0)
- Carpool option (Boolean - true/false) **[12]**
- Available carpool seats (int >= 0) **[12]**

AGENT VARIABLES

Secondly, the agent-specific variables are presented. These variables are as well accompanied by a number that refers to the assumptions and/or initial parameter setting they are based on. These respective assumptions and parameter settings can be found in appendix A.

Student has:

- Competences (list) **[3]**
- Affordances (list) **[3, 22]**
- Importance connected to values (table - continuous scale from 0 to 10) **[4]**
- Personal beliefs (table - continuous scale from 0 to 10) **[5]**
- Shared beliefs (table - point scale) **[6]**
- Reference group of co-oriented peers (agentset >= 0 agents) **[7]**
- Prosociality (int >= 0) **[8]**
- Willingness to cooperate **[10]**
- Relation with other students: **[11]**
  - Influences strength (int >= 0)
  - Similarity (point scale) **[2, 4]**
- Travelsatisfaction (int) **[13]**
  - Travel-related stress (int >= 0)
  - Travel-related enjoyment (int >= 0)
  - Intrapersonal comparison (int >= 0)
  - Social comparison (int >= 0)
- Activity implementation history **[14]**

As aforementioned, additional information on the functioning of each variable can be found in appendix A. However, a few of the variables will be discussed more in-depth in this section.

First of all, by their **personal beliefs**, students give a specific relation strength to the connection between transport modes and values. In other words, the connection between every value and transport mode is different for each agent. The beliefs on this value-transport mode connection is represented by a point scale with points varying from 1 to 10. The higher the points given to the connection, the higher the belief in this relation. So, for example agent X think flexibility is linked the most to biking (value = 7.9), then the car (rank-value = 4.8) and then the bus (value = 1.2). A continuous belief-scale has been chosen for two reasons. First of all, because it is substantiated as a good method to capture opinions by both Deffuant et al. 2000 and Hegselmann et al. 2002. A continuous opinion scale is within these studies argued to be an approach that keeps compromising in the middle as a plausible alternative for agents. The second reason for choosing an continuous scale within this study, is to ensure agent heterogeneity despite the fact that each travel type is represented by more than one agent. This way, agents from different types can still see each other as co-oriented peers. Nonetheless, the beliefs on relation between activities and their competences and affordances as presented in 3.1 are not agent-specific, as personal beliefs do not apply for these activity requirements. Thus, for example having a car available for being able to choose the car as a transport mode, is a set rule for every agent in the model. This is a simplification of reality, as some individuals might find that they can drive without a license. This simplification will be elaborated upon in the discussion section in Chapter 7.

Another aspect of agents' **personal beliefs** is that is considered a private characteristic within the model. Chapter 2.4 elaborated upon the possibility of agents comparing themselves based on private or public characteristics. Within this model, agents compare themselves through private characteristics such as their values (which determines whether they find themselves co-oriented or not) and beliefs (which determined the adjustments within their own beliefs). In this model, public characteristics are the actions taken by agents (decisions for transport mode), which are not directly adopted by agents. Thus, agents compare their own private characteristics with other agents' private characteristics and also adjust their own private characteristics accordingly. Public characteristics do not account for comparison material **[23]**, but because of shifting private characteristics, these can become more similar.

Furthermore, the **relation between agents** is built over time when agents find themselves co-oriented regarding their values and when they are both (intermediately) prosocial. As described in chapter 2, this approach is known as similarity biased influence. Similarity biased influence is a well substantiated basis for social interaction within the field of opinion dynamics and has therefore been chosen to form the foundation of social comparison within this model (Moschis, 1976; Teşileanu & Meyer-Ortmanns, 2006). When agents find themselves co-oriented, the bond between agents starts increasing in terms of influence-strength. This means, that agents who have a strong relation, will adjust their beliefs to a higher degree than agents who have just started to build their relation **[15], [16]**.

Lastly, the **travel satisfaction** is a product of travel stress, -enjoyment, intrapersonal- and interpersonal (social) comparison (Abou-Zeid & Ben-Akiva, 2011) **[13**. The equation representing these dynamics is presented in Eq. 4.1, which is based on Abou-Zeid & Ben-Akiva's equation on commute satisfaction.

$$S = \beta_1 * TE - \beta_2 * TS + \beta_3 * SC + \beta_4 * IC \tag{4.1}$$

Here, S is the Travel Satisfaction, TE is the Travel Enjoyment, TS is the Travel Stress, SC is the social comparative travel satisfaction and IC is the intrapersonal comparative travel satisfaction. The constants in this equation represent the importance an agent attaches to each satisfaction-component. For example, an agent might choose a very stressful transport mode (according to its own beliefs), but might not find stress an important indicator for its transport satisfaction.

4.2.2. BELIEF ADAPTION MODEL UNDER TOM-RESTRUCTED INFORMATION TRANSPARENCY

For the ToM-restricting model, the application of the three opinion dynamics components, all global- and most agent variables as mentioned in the previous section are present. There is one agent variable added to the model:

- Theory of mind capabilities (point scale) **[9]**

Through agents' ToM capabilities, the accuracy of prediction of others' values, beliefs and travel satisfaction is affected. The better the ToM-capabilities, the closer these predictions are to the real private characteristics of other agents. This deficiency is represented in the model by equation 4.2.

$$E = R + (or-)\mathcal{N}(\mu,\sigma^2) \tag{4.2}$$

4

Where E is the estimated value (of belief, value or travel satisfaction) for another agent, R is the real value (of belief, value or travel satisfaction) and the normal distribution added to this real value provides the error obtained by ToM-restrictions. The better the ToM-capabilities of an agent, the lower the mean (μ) of this normal distribution. Furthermore, σ represents the standard deviation that an agent can deviate from the mean value. This uncertainty in prediction gets higher as the ToM-capability gets lower. This error in prediction calculated from the normal distribution can subsequently be added or subtracted from the real value (R). Some agents have the tendency to overestimate, and consequently add the error to the real value. Other agents have the tendency of underestimating situations, and rather subtract this error from the real value. In other words, the prediction of agents on other agents beliefs, value and travel satisfaction depends on their ToM-capabilities and whether they are an over- or under estimator.

Figure 4.4 presents the global- and agent- variables present in the model, their attributes and links. This is an overview where the relation between the most important variables is schematically displayed, which helps understanding the different information flows and processes. The for the ToM-model added component is highlighted by the blue cloud.

4.3. MODEL FORMALISATION

The conceptual model is formalised in order to be implemented in NetLogo. Incorporating social interaction will contribute to the systems' complexity. This section describes how this complexity is handled by formalisation of the concepts as described in section 4.2.

4.3.1. DEVELOPING A MODEL NARRATIVE

With having explained the different concepts embedded in this study, this section described how these different concepts play a role in the processes executed in the model. Four phases can roughly be distinguished in the model; the sense-, decide, act and update phase. Figure 4.5 presents the most important processes that find place in each phase, with personal and social oriented processes separated. The components added for the ToM-model are highlighted in blue. In the sense phase,agents scan their physical

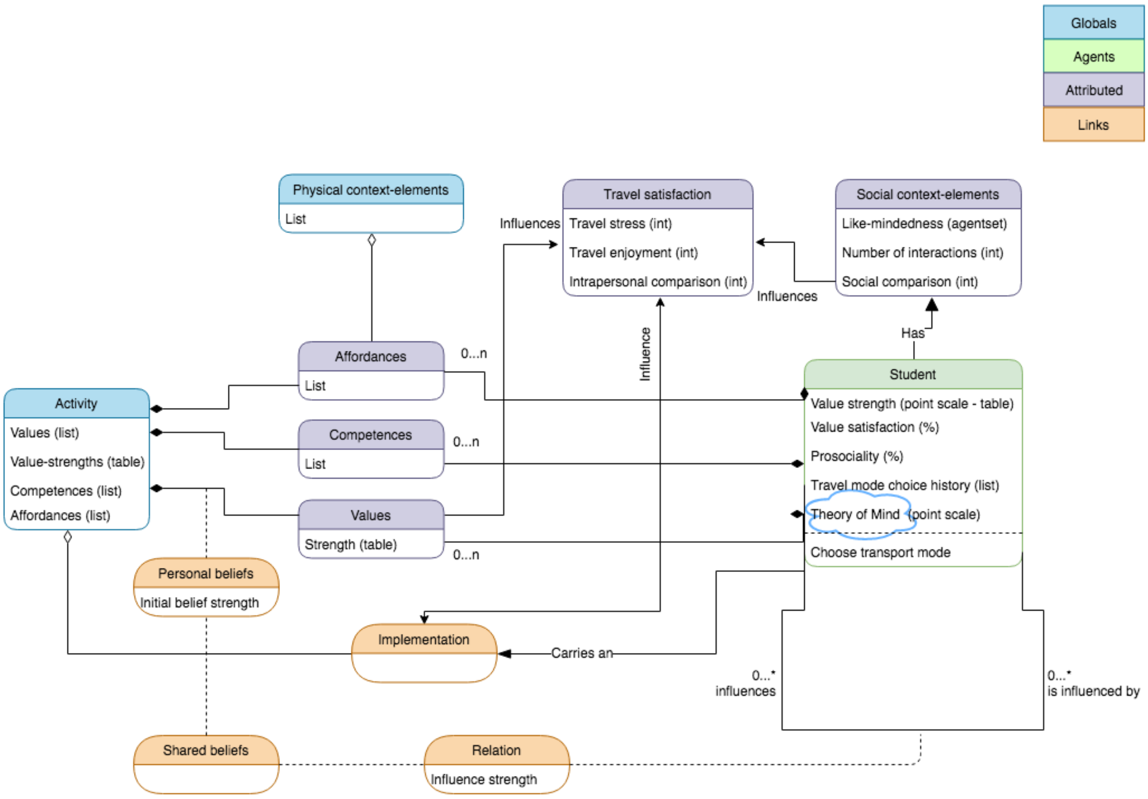

Figure 4.4: UML

and social environment. Agents gather information about what they find important in terms of values and beliefs and what others in their environment find important. Then, in the decide phase, agents found their decision on their personal and social based preferences and on the conformity between activity required elements, personal belongings and options to share belongings. In the following process, agents will act upon this decision and form their preference. In the last phase, agents will update their personal and social elements, resulting in adjusted beliefs. A more elaborate explanation of each process can be found in Appendix B.

4.4. CHAPTER SUMMARY

This chapter presented the three models; a belief-adaption model with full information transparency, a belief-adaption model with ToM-restricting information transparency and a action-adaption model. The first two models are designed and created within this thesis. For these models, firstly a conceptual model is presented. The concepts used within this conceptual model are hereafter formalised, preparing them to be implemented into an agent based model within the NetLogo environment. As a result, a formalisation of the model can be presented, devided into a sense, decide, act and update section. The processes that are most characterising for the models designed within this study, are the selection of available transport option through "practical consciousness", followed by a personal and social evaluation of the implemented action based on personal beliefs, which can flow into shared beliefs through social comparison and

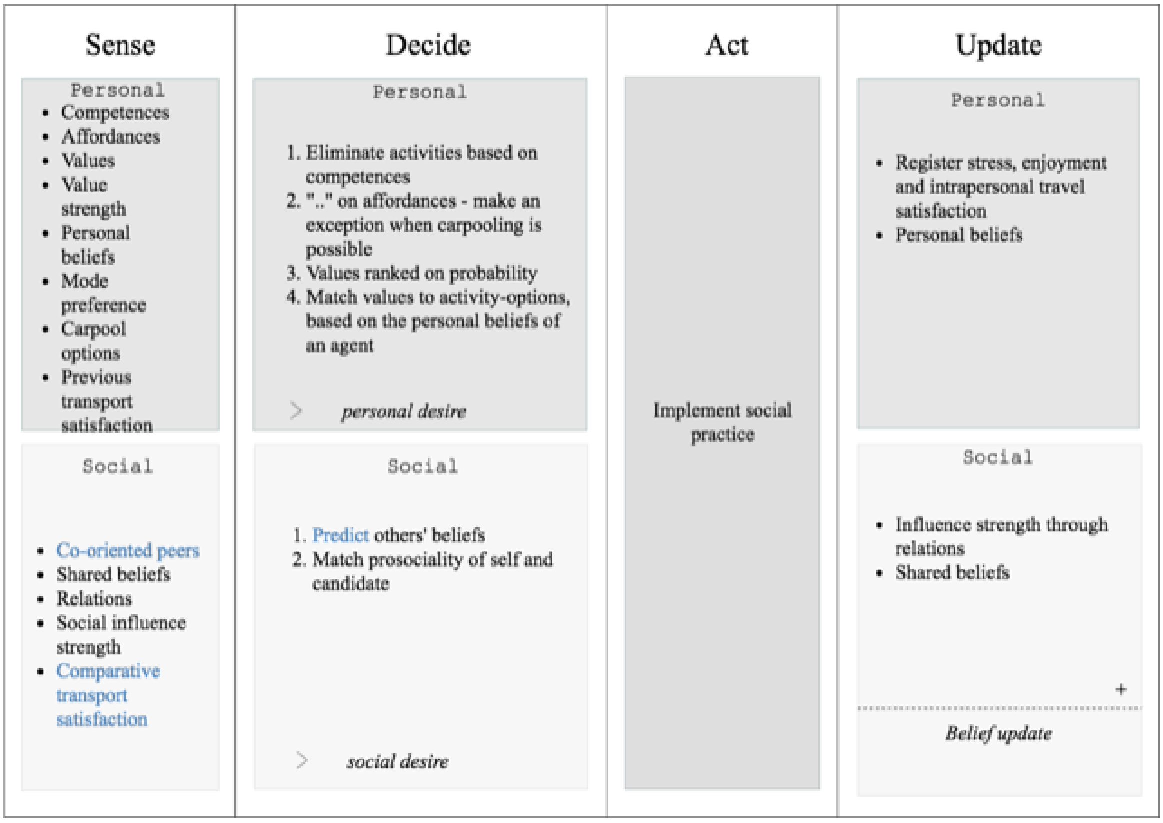

Figure 4.5: Overview of the processes in the model

influence.

4

5

MODEL VERIFICATION, VALIDATION AND SENSITIVITY ANALYSIS

"The computer is not, in our opinion, a good model of the mind, but it is as the trumpet is to the orchestra - you really need it."

- Gerald Edelman

After formalising and implementing the model, verification and validation of the model is required. This model is designed for explanatory purposes, which can only be served with a verified model. First, the verification of the model is presented. For this study, Sargent's (2008) definition of verification is used, which states that verification involves "ensuring that the computer program of the computerised model and its implementation are correct". Subsequently, the validation process for this study is presented. Validation in this study is used as “substantiation that a computerised model within its domain of applicability possesses a satisfactory range of accuracy consistent with the intended application of the model” Schlesinger (1979). Lastly, sensitivity analysis is executed to determine which input variables have most influence on the output of the model. With the verification, validation and sensitivity analysis, sub question 3 will be answered: *"How can the realism of the agent-based model with a social influence component be evaluated?"*.

5.1. MODEL VERIFICATION

In order to reassure that the concepts used to describe the analysed system are formalised and implemented correctly in NetLogo, structured walkthroughs and traces are performed. This paragraph contains the verification of all model requirements as specified in chapter 3.2. Sargent (2010) describes two approaches for verifying computer models: static testing and dynamic testing. For static verification, the model is tested analytically, without simulation. For dynamic verification, small experiments will be conducted under different conditions to test whether the model produces consistent outcomes.

5.1.1. STATIC VERIFICATION

The following requirements are tested statically:

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- **A2: Agents can scan their social and physical environment**
  Confirmed - agents are aware of their physical capabilities and requirements for certain activities and know which other agents belong to their reference group. According to these observations, agents can be restricted from executing actions and agents interact with others they find to be co-oriented.
- **A3: Agents have a theory of mind**
  Confirmed - The better agents' ToM-capability, the better their prediction of the beliefs of others, which affects agents' shift in belief over time. That is, a better ToM-capability leads to fewer fluctuations in beliefs.
- **A5: Agents have a level of prosociality**
  Confirmed - the more prosocial, the more effort agents will put into social connections. They will be more willing to revise their beliefs and adapt them according to the views of co-oriented peers, provided that the agent subjected to the interaction is also (moderately) prosocial.
- **C1: Reference group**
  Confirmed - agents form a group of in their perception co-oriented peers. These reference groups are represented in the visualisation through clustering of agents (figure 5.1).
- **B1: Agent beliefs** *Confirmed* - agent beliefs change of time through social interaction and -adaption and through personal travel-satisfaction evaluation.

5.1.2. DYNAMIC VERIFICATION

The following requirements are tested dynamically:

- **SP1: Social practices form rules for social interaction**
  Confirmed - the elements of a social practice determine which competences, affordances and value-appreciations are necessary for an agent to implement an activity according to it's beliefs. First of all, agents have a certain attitude towards social

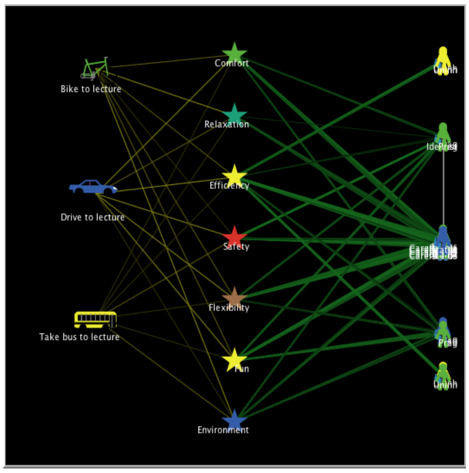

Figure 5.1: Model interface; the visual representation

practices. This attitude is translated into their beliefs (e.g.; "The bike is a transport mode with high flexibility). Now, agents that are co-oriented can compare these attitudes and re-consider their own. Indirect, social influence is also affected by social practice elements "affordances" and "competences". A change in these elements causes a change accessibility of practices, consequently of personal evaluation and thus in beliefs. This influence of accessibility of social practices on agent beliefs has been tested by adding a switch to the agent-based model. This switch allows all agents to have access to a car. To make the contrast between practice availability and unavailability clear, before the switch is turned on no agent has access to a car. When this switch is turned on, there can be seen that more agents choose the car as their preferred mode of transport. Because of this, agents evaluate the car more often as a mode of transport, on a personal and social level. Before making the car available for every agent, beliefs on car - value relations were not compared and adapted because of 'irrelevance' concerning evaluating a transport mode that is not an option. This leads to all agents being zealots concerning car - value beliefs. Figure 5.2 shows that as soon as the switch is turned on (at t = 100), agents start adapting their beliefs (through personal and social evaluation). In short, the rules presented by social practices are followed by agents, which leads to a different social environment of the agent.

- **A4: Agents influence each other**
  Confirmed - by comparing their own beliefs with beliefs of co-oriented peers, agents can adapt their beliefs. This is tested by changing the similarity threshold (the maximum difference in values within which agents can still consider themselves as co-oriented). When this is set to zero, and thus when agents never get the chance to see themselves as co-oriented, the beliefs of agents change less over time. There is still some fluctuation in beliefs, but this is because of the personal evaluation of agents.

- **CP1 & Af1: Competences and affordances** *Confirmed* - agents have a list of activ-

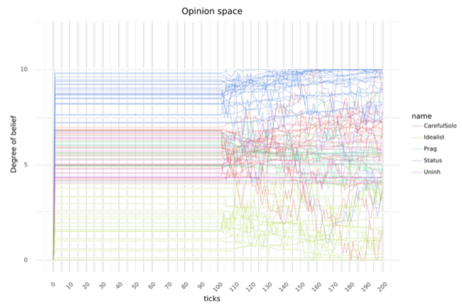

Figure 5.2: Beliefs on car - fun relation with no agent owning a car (t = 0 - 100) and all agents owning a car (t = 100 - 200)

ities they are not able to implement because of their lack of competences and/or affordances. Consequently, they do not implement these activities. This is illustrated by figure 5.3, where firstly no agent had a car, leading to no agent beging possible to choose this transport mode. At tick 100, every agent had a car, leading to the share agents preferring the car rising.

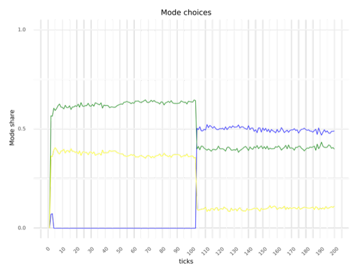

Figure 5.3: Mode shares with no agent owning a car (t = 0 - 100) and all agents owning a car (t = 100 - 200)

- **Personal evaluation of chosen transport mode**
  Confirmed - Agents evaluate their decision according to the four pillars (social- and intrapersonal comparison, stress and enjoyment). Agents determine their travel-satisfaction accordingly, and adapt their believes on the transport mode subjected to the evaluation. By doing so, through a learning mechanism their choices eventually are influenced in a way that causes their travel-satisfaction to moderately rise (see figure 5.4).

- **Carpooling** *Confirmed* - Carpooling is possible when an agent peferres to take its car and allows four others to join. The possibility of carpooling can be switched on and off in the model. The differences in agent behaviour in the model is clearly present under different carpooling conditions. With the switch on, more agents choose the car as a transport mode than when this switch is turned off, which can be identified by a raise in the share of car users (figure 5.5

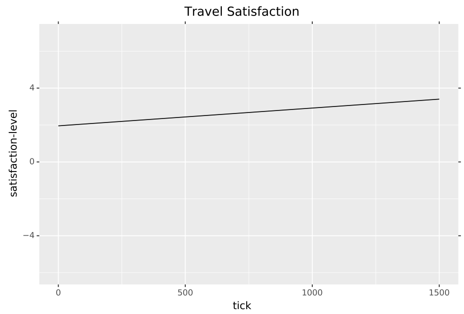

Figure 5.4: Travel satisfaction over time

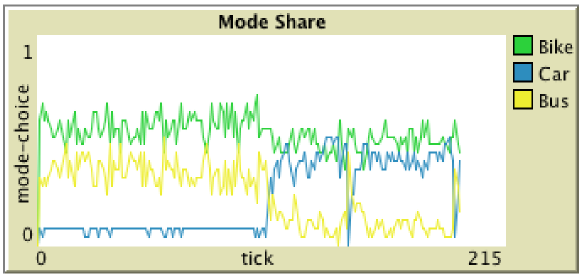

Figure 5.5: Raise in car usage when carpooling becomes possible

5.2. VALIDATION

The structure of this paragraph is built from two sections; conceptual model validation and operational model validation. The conceptual model presented in figure 4.2 will be subject of validation. The conceptual model will be inspected for correct underlying theories and assumptions and if the representation of the captured system is "reasonable" (Sargent, 2008). In the section of the operational model validation, there will be described how and to what extend the output of the simulation model is accurately resembling real world behaviour of the system subject to this study (Sargent, 2008).

5.2.1. VALIDATION OF THE CONCEPTUAL MODEL

The conceptual model of figure 4.2 exposes the assumptions and theories that form the basis of the operational model. Since there is no standard or proven way of implementing these theories, this has been done in a through this research designed manner, summarised in the conceptual model. The elements of the social practice theory, theory of mind and social interaction through comparison on the basis of similarity are all included in this model. The validity of the connections between these elements is determined through Face Validity. How these theories are connected, is presented in a high level overview presented in figure 5.6.

Figure 5.6 shows three links between the theories used in this study. The theory of mind is linked to the social practice theory, as it restricts agents from having full insight into the beliefs other agents have on social practices. This influences social interaction as performed by the rules of social practice theory. Social practice theory is then connected to social interaction through comparison on the basis of similarity. The social

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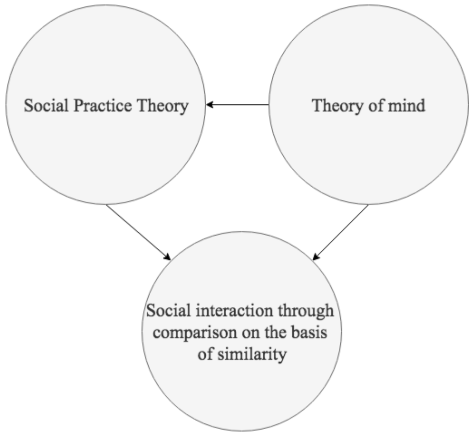

Figure 5.6: Connection between theories in the conceptual model

practice theory creates the rules for processing elements of the physical world and internal system of agents. This shapes the reference point agents use to compare themselves to others.

Intuitively, the connection between these theories and the elements which are connecting them seem to give a correct representation of the system. However, since these theories have not been combined in earlier studies, this approach cannot be compared to previous studies. This means that coherence within the theoretical framework cannot be guaranteed in this study and cannot be validated yet. This will be further discussed in chapter 7, the discussion.

5.2.2. VALIDATION OF THE OPERATIONAL MODEL

Sargent (2013) defines two components of operational model validation: (1) an extreme condition test and (2) an output comparison to relevant data. Both are described in this section.

5.2.3. EXTREME CONDITION TEST

The extreme condition test is executed by varying the models parameter settings with large variances, in order to check whether the model behaviour is in line with its behaviour under initial settings. Four variables will be varied; the group size, similarity threshold, percentage of bike-owners and lastly the percentage of car-owners. 5.1 shows the variations in variables and whether there were any boundaries that occurred.

As can be concluded from table 5.1, the stated variables can have of a wide range of inputs, without causing any errors. Needless to say, percentages are limited between 0 and 100, but other than this there are no further boundaries to be mentioned. For the share of agents owning a bike or car, straight forward predictions can be formed on the effects of varying these variables. That is, a larger share of agents owning a transport mode, leads to more agents considering this as an option and respectively preferring this mode of transport. Just as described in the verification of the agent-based model, this causes agents to evaluate the mode of transport and adapt their beliefs. This reaction to variance in the percentage of transport mode owners is according to the prediction for all

Input variable	variation of value	Limitations
Group size	min: 1, max: 150	None
Similarity threshold	min: 0, max: 50	None
Percentage of students with a bicycle	min: 0, max: 100	None
Percentage of students with a car	min: 0, max: 100	None

Table 5.1: Exterme value test for the operational validation of the model.

(extreme) values. For the group size and similarity threshold, forming expected model behaviour under higher or lower values is more complex. Nonetheless, when extreme values serve as input for these variables, their behaviour under initial parameter settings is strengthened and respectively weakened without inconsistency. Therefore, these variables also pass the extreme condition test.

5.2.4. OPERATIONAL VALIDATION

The next step for the verified agent-based model, is operational validation. For the operation validity of social simulations, it is needed to compute the degree to which the model resembles the social processes within the real-world social system. For operational validation, ideally the outcomes of a data-driven model are held against real-world data of the system with matching components in the same context, in order to examine the rate to which the model resembles the real system. For this research, operational validation would also require some sort of reference point, preferably in the form of data. However, because of the complex nature of social systems, for models that aim to capture those systems it is a challenge to attain suitable material for operational validation (Yilmaz, 2006). This challenge mainly arises because of the complex nature of human actions (Sun & Müller, 2013). There is no 'gold standard' for models of social oriented topics, since there is no golden standard for human behaviour. As a result of limited knowledge, biases and strong heterogenity, rationalism and consistency within human behaviour can often be questioned (Sun & Müller, 2013). Consequently, the creation of rational and consistent agents also becomes a challenge.

Besides the complexity of validating MAS and agent-based models in general, extra complexity arises within this study since there are no other studies that have tried to to capture the same social constructs into a simulation. Therefore, this model is vulnerable when it comes to the perspective of its designer. The choices that have been made are partly based on literature, but when literature was absent, assumptions based on intuition have been included. This increases the chances of the model maker's biases towards to topic to be included in the model. In the next paragraph the most challenging subsystems of the model are discussed. However, as stated by (Sargent, 2013), when validating a model, the purpose of the model must not be forgotten. As aforementioned, this thesis can be read from a multi-actor perspective and from an agent-based perspective. The complexity arising from validating social-oriented models has different implications for these two approaches. Firstly, from a multi-actor perspective, the purpose of the model is to contribute to the development of sociality within simulation studies. This system-development requires a benchmark to determine whether or not improvements are made. Without this benchmark, operational validation of the model and thus determining the quality with which the designed system contributes with to the field of MAS remains impossible. Secondly, from an agent-based perspective, the purpose of this model is to provide insight into human social behaviour. A not operationally validated agent-based model, means that the behaviour produced by agents does not necessarily correspond to real world behaviour. This makes it difficult to derive statements on human behaviour in the real world through analysing results. In conclusion, for both perspectives this thesis can be read from, the challenge of validating the agent-based model poses a problem. This is considered as a shortcoming within this thesis which cannot be neglected when analysing the results of the agent-based model. Thus, the lack of operational validation needs to be kept in mind when using, building on and expanding this study.

Aside from the lack of possibilities of validating the macro-behaviour of this model, there are three constructs within the model that pose an extra challenge towards validation. This section zooms in to these three constructs.

First of all, the openness of the system with respect to agents outside of the group of students travelling from faculty to seminar. In the real world, agents will not only be influenced by their class mates, but will encounter many other opinions throughout the period between the respective classes. This means that for example the clustering of opinions, will happen in a different manner than how they result from the model now, as this can be disrupted or stagnated. This is an aspect that will always be part of the challenge in simulating social interaction and opinion dynamics and cannot be fully realistic. However, the model can be tested on its reaction to noise and sudden opinion shifts in order to analyse the validity of the response to such events. It would not be possible to exactly know which response should be looked for, but certain boundaries that are considered reasonable can be set, which leads to invalidation when the model outcomes exceed those boundaries after an event. Because the knowledge necessary for this validation process could not be obtained within the time-limits of this research, this is proposed as future work (Chapter 9).

The second construct within the model that poses an extra challenge towards validation lies within the personality of agents. At this moment, five different personality types with respect towards travel modes, their prosocialness and ToM-capacity have been classified. However, the complexity of personality and how this affects all other components in the model has not been fully captured. For example, stubbornness, trust, social history, self-esteem, spontaneity, extroversion and so on, are all concepts that influence social interaction, but that are not captured in the model and that would be difficult to include. However, posing conclusions on the sociality of agents who are not completely social might result in a paradoxical situation, complicating the agent-based oriented purpose of this thesis. Therefore, for the validation of the behaviour of agents, more insight would be needed on the meaning of including certain social aspects and leaving others out, in order to distinguish behaviour that is a result of the applied theories, and which behaviour is steered by the specific social rules that have been applied, which would have been different when other concepts where introduced. This is a challenging process, which requires more research in other fields such as int he field of psychology and sociology. Therefore this is not included in this research, but more value would be added to this study if the knowledge around these constructs increases in the next couple of years.

Lastly, the social stability of the model is the last model-component which makes the validation of model behaviour difficult. In reality, besides the internal system of individuals, also their mutual relationship is subject to capriciousness, as the current emotions and mood of an individual can affect the persons they would like or would rather like not to interact with. Even more rigorous situations where agents are irritated by a specific other agent and stop interacting over a couple of encounters are not uncommon. In this model, the agents are always open to interact with and anticipate on other agents within their social network. This could stimulate clustering and can therefore interfere with the model behaviour. As the model analyses the affect of implementation of certain theories on social influence, this affect might result in stronger results because of the stable social relationships. Therefore, for the validation of the model, it is important to be aware of the implications of this social stability, and what might be different when the relation between agents would include certain amounts of instability. Because of time restrictions, this cannot be executed during this research, but knowledge on this item would increase the degree to which one can find this model valid or not.

With the rise in popularity of agent-based models, more research about new, more appropriate ways of validation have been a topic of interest (Louie & Carley, 2008; Yilmaz, 2006; Sudeikat et al., 2006). For now, non the the proposed standardised modules for validation can be applied to this specific study. However, with the dynamical progresses made within this field, chances are big that the challenges discussed in this paragraph are encountered in more researches and more general approaches on how to validate socially embedded systems might be developed. For now however, the degree of consistency between the model and society remains an unknown factor. The value of this model, despite the challenges around validation, are discussed in more detail in chapter 9 where is elaborated on the scientific relevance of this study.

5.3. SENSITIVITY ANALYSIS

Through sensitivity analysis, the variance in output variables as a result of varying input variables are examined (Saltelli et al., 2010). This way, the variables that cause the biggest fluctuations in model results when adjusted can be identified (Sun & Müller, 2013). In other words; the inputs that are most important for the outputs.

This sensitivity analysis serves two purposes:

- Multi-actor system perspective: determining the extend to which model outcomes are influenced by variance in input variables. Input variables with a high contribution to output variance form the largest uncertainty for the output of the model. When little is known about the exact value these influential input variables should have in the model, this causes an increase in the uncertainty of the model.The amount of influential variables also presents insight on the robustness of the model.

- Agent-based perspective: determine which input variables have a significant influence on agent behaviour, and would be interesting to zoom in to through experimenting.

This analysis will be performed both for the model with and without full information transparency.

There are many techniques for the identification of the influential variables with respect to output variables of interest. For this study, global sensitivity will be used. Within global sensitivity analysis the full spectrum of values that serve as input for the model are taken into account when examining the output uncertainty (Homma & Saltelli, 1996). On the other end of the spectrum is "one-a-a-time" sensitivity analysis, where one value is analysed at a time with respect to changes in output (Jaxa-Rozen & Kwakkel, 2018b). Saltelli et al. (2008) states that through global sensitivity analysis, there can be contributed to the robustness and parsimoniousness of the model, which makes this analysis akin to the validation of the model. Global sensitivity analysis can however be computationally heavy since it does not only asses first order affects of changes in variables, but also their interconnectedness and thus second or even higher order affects of slight changes (Jaxa-Rozen & Kwakkel, 2018b). For this reason, Jaxa-Rozen & Kwakkel (2018b) stress the importance of using a tool that reduces the required time and costs for global sensitivity analysis, and propose variance based Sobol indices as an alternative. Sobol indices can help capturing each parameter's contribution to model variance (Jaxa-Rozen & Kwakkel, 2018a). Using variance decomposition, first-order and total Sobol indices are calculated in order to present the fractional contribution of individual variables and respective indirect contributions. In total, there are three different Sobol indices per input variable that indicate the importance in output variance:

1. First order index (S1): the amount of variance the variable contributes on its own.
2. Second order index (S2): the amount of variance the variable contributes through other variables.
3. Total effect (ST): the amount of variance the variable contributes on its own and through other variables.

For the execution of this analysis, Jaxa-Rozen & Kwakkel (2018a)'s PyNetLogo tool has been used. This tool allows the NetLogo model to be linked to Python, for a direct execution of more complex analyses for the agent-based models. Within the PyNetLogo tool, the SALib Python library is used for the global sensitivity analysis with Sobol indices (Herman & Usher, 2017). Additionally, the ipyparallel library is used for parallel execution of the sequential simulations to further contribute to the aim of performing the global sensitivity analysis within a time-efficient method.

With this focus on time efficiency, factor prioritisation is used to select the input variables that are of highest interest. As Leamer (1985) stated: "A fragile inference is not worth taking seriously". For this reason, the variables which have proven to have little to no influence on the variance of output variables are not described in this chapter. Also, the input variables can be devided into two categories: (1) variables which are fully case dependent and thus which outline the scenario and (2) variables which are not set to one specific value yet because little is known about this yet. The latter will be the focus point of this analysis. The reason for this, is that the scenario dependent input variables can be determined by a thorough examination of the case: the number of students present, the percentage of them having a car and the percentage of them having a bike. As can be seen from the description of the complete sensitivity analysis in appendix D, these category I variables can not be neglected when it comes to the sensitivity of the model, as they have a significant contribution to the variance of the output variables. Within this type of variables, the number of students input variable appears as the most influential. Moreover, the first category is also relevant for the agent-based perspective within this study, as it is interesting to later experiment with these input variables and determine the effect on agent behaviour. However, the input variables of the category II have been put to values that intuitively felt correct, but that have not been substantiated yet because of a gap in the research. Without more knowledge on the boundaries in which these values most possibly occur, little can be said about the current values they have been set to. Therefore, a large contribution of these input variables to the variance in output, would mean that this large uncertainty affects the entire model and maybe even steer the results into an unrealistic path. Because of this, this chapter has special attention for specific variables for both the sensitivity analysis executed for the model with full information transparency and for the model with restricted information transparency. This approach related to the multi-actor system approach of this thesis. For a full overview of the entire sensitivity analysis for both models, appendix D can be consulted.

5.3.1. SENSITIVITY ANALYSIS FOR THE MODEL WITH FULL INFORMATION TRANSPARENCY

First of all, the model where agents have full insights into the beliefs, values and travel satisfaction of other agents in order to make up their own mind is subjected to the sensitivity analysis. For the results of this sensitivity analysis with all input variables, with appendix D can be consulted. With this in mind, the input variables in table 5.2 have been selected for sensitivity analysis. These input variables have been selected to present in this section, as they appear to have the largest contribution to the variance of certain output variables. An explanation about the decision for the boundaries of these variables can be found in appendix D.

Input Variable	**Variance range**
Similarity threshold	[5, 25]
Influence: Speed of increase in influence strength	[1, 5]
BeliefUpdate: Adjustment of beliefs towards beliefs of others through one update moment	[0.05, 5]

Table 5.2: Input variables subject of sensitivity analysis

The output variables for which the variance as an affect of shifts within these input variables has been analysed are the following:

1. Sizes of reference group: The average size of groups of students who find them-

selves alike and influence each others beliefs.

2. Average change in beliefs: The average change in belief points as a result of single evaluation.

3. Percentage of students who are socially influenced

From the Pearsson correlation test can be concluded that all output variables are relatively strong correlated to the number of students (figure 5.7 to 5.9). Despite the fact that this is a category 1 input variable, and thus is not of special interest for this analysis, this information should be taken into account when setting up the model for a specific case. A correct resemblance of the amount of students present, is of great importance for the output of the model.

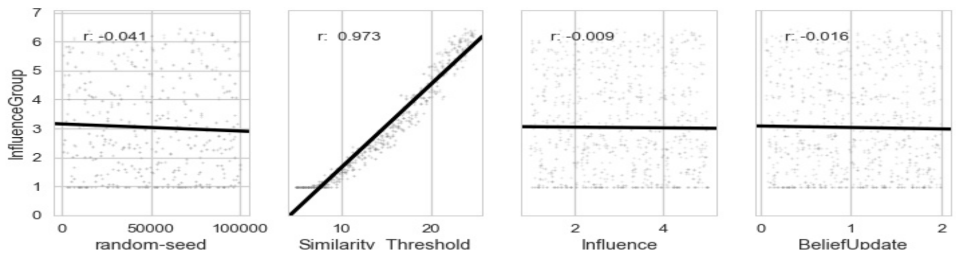

Figure 5.7: Pearson correlation between input variables and the average size of reference groups

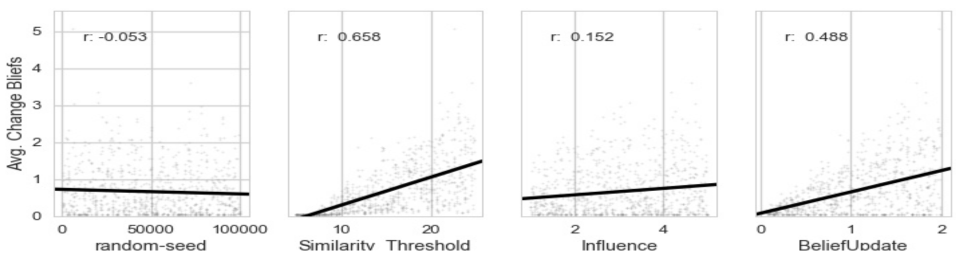

Figure 5.8: Pearson correlation between input variables and the average change in beliefs during each evaluation process

besides the number of students, the output variable "Average shift in beliefs per evaluation moment"is the variable most sensitive to fluctuations of several input variables. The other output variables can be considered relatively insensitive to variations in the other input variables, as the correlation between input and output variables is negligible. Therefore, this output variable is hold as the centre of attention during the rest of this sensitivity analysis.

Figure 5.10 gives an overview of the contribution of each input variable on the variance of the change in beliefs as an output variable, and also of the interaction between these input variables. The size of the black circle indicated the individual contribution of the input variable on the respective output variable. The white circle indicates the higher order effects of the input variable on variance in the respective output variable.

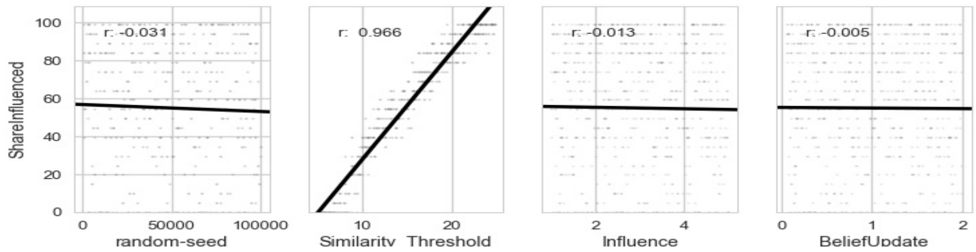

Figure 5.9: Pearson correlation between input variables and the average number of socially influenced students

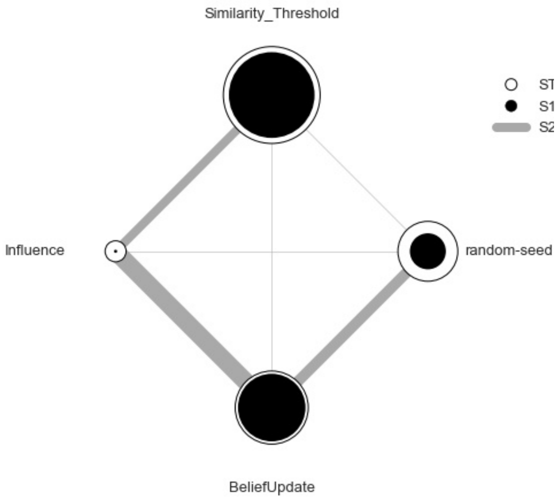

Figure 5.10: Individual influence, higher order influence and interaction between input variables on the average change in beliefs in one evaluation moment

When the outcomes of the sensitivity analysis as they are presented in figure 5.10 are analysed, a few aspects stand out. First of all, the largest contribution to output variance is provided by the input-variable "Similarity_Threshold", followed by "BeliefUpdate". The contributions of these input variables are for the largest part by direct influence, as the circles are predominantly black. The input variable "Influence" however, is black for just a fraction of the circle surface. This can be explained by looking at the connections between input variables. As can be seen, the input variable "Influence" is connected to both the "Similarity_threshold" and "BeliefUpdate" input variable. Through interaction, these input variables influence the value of "Influence", which in its turn influences the average belief shift for every evaluation moment. On its own, this input variable does not contribute to much variance in the output. Lastly, the random seed also contributes to a part of the output variance. Therefore, no matter how certain the values given to the input-variables, the model will always carry a certain level of uncertainty. In short, variance within this output variable is mainly subjected to the "Similarity_threshold" and "BeliefUpdate" input variables, which also have the ability of strengthening or weakening each others value. This makes this output variable more uncertain, and with this output variable also the model. Thus, from a multi-actor system perspective, these two input variables cause most uncertainty within the full-information transparency model and are thus most critical. From an agent-based perspective, besides these variables, the number of agents present in the simulation is also a relevant variable, as despite the fact this is only determined by the scenario, this can still cause different behaviour of agents to occur. Therefore from an agent-based perspective, the average points beliefs are updated with, the similarity threshold and the number of students present in the simulations are interesting to further experiment with.

5.3.2. SENSITIVITY ANALYSIS FOR THE MODEL WITH A RESTRICTED INFORMATION TRANSPARENCY THROUGH DIFFERING THEORY OF MIND CAPABILITIES

For the model where agents do not have full insights into the cognitive system of other agents, the same sensitivity analysis has been performed. There has been added one input variable to this sensitivity analysis; the average miss estimation that agents have when estimating the beliefs of others. This variable differs from 0.1 up to 4 points.

Again, first the Pearsson correlation coefficients (r) are computed for analysing the correlation between each input- and output variable. As can be seen in figure 5.11 to 5.13, there is shown that in contrast to the model with full information transparency, for this model the output variable "Average shift in beliefs per evaluation moment" is not correlated to any of the input variables. This means, that although an input variable has a high Sobol index, this implies that is has a high contribution to a negligible correlation, which does not have a significant influence on the output of the model. A reason for this lack of correlations for this output variable might be found in the fact that belief-forming of agents is subjected to more uncertainty in the ToM-model, and will fluctuate more over time per definition. Subsequently, this fluctuation might be harder to influence through input variables than belief dynamics that are following one vast pattern. For this reason, this output variable will be left out of scope for the rest of the sensitivity analysis for this model. Another input variable with strong correlations to the output variables, is the mean deviation of agents.

Furthermore, from the bivariate scatterplots can be concluded that the number of students again has a strong correlation with the output variables, and as stated in appendix D, has a strong first order contribution to the variance of output variable "Average reference group size" and "Average share of influenced students". However, this category 2 input variance is not the main focus of this model. Therefore, there is recommended that this is taken into account when setting up the model, but this input variable is not included with presenting the rest of the results.

Figure 5.14 presents the results for the Sobol sensitivity analysis for the model where information flows are limited by ToM-capacity. As the results of this analyses are very similar for both output variables of interest, with respect of the selected input variables, figure 5.14 represents the outcomes for both the "Average size of reference groups" and for "Average share of influenced students". From this figure there can be concluded that the similarity threshold has the larges contribution to variance in the output variables. The mean deviation however also has a significant share in this contribution. Just as

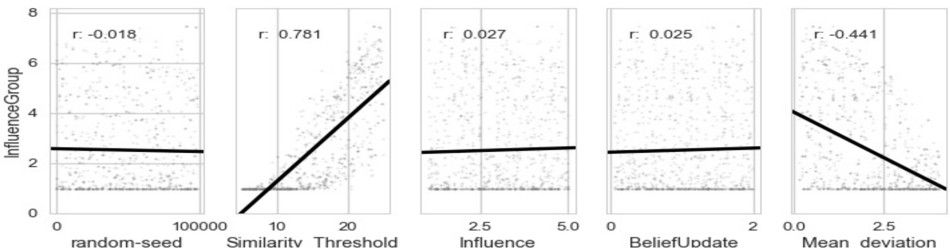

Figure 5.11: Pearson correlation between input variables and the average size of reference groups

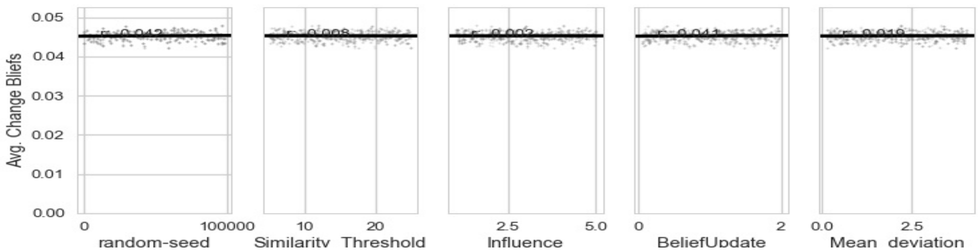

Figure 5.12: Pearson correlation between input variables and the average change in beliefs during each evaluation process

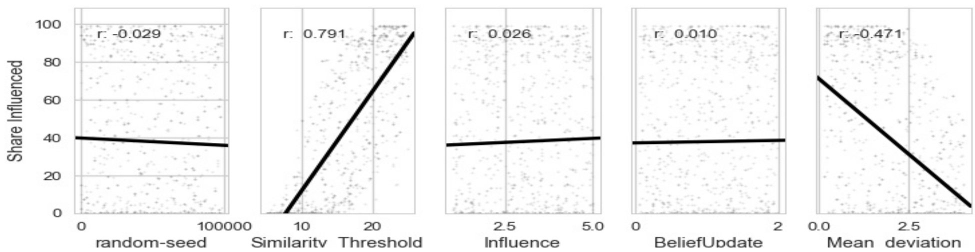

Figure 5.13: Pearson correlation between input variables and the average number of socially influenced students

with the model with full information transparency, the random seed also has a relatively small but not to be neglected contribution to output variance.

In conclusion, from a multi-actor system perspective the sensitivity analysis for the theory of mind model presents the input variables "Similarity threshold" and "Mean deviation" to have the largest contribution to variance in the output variables "Average size of reference-group" and "Share of influenced students" and thus generate the most uncertainty. Thus, the model with and without full information transparency both have different in- and output variables which contribute to their sensitivity. This difference in sensitivity can only be a result of a difference within the social comparison processes of the models. From an agent-based perspective, alongside the mentioned input variables that cause output variance, the effect of the number of students present in the model is also an interesting input variable to include in further experiments, as group size also affects agent behaviour.

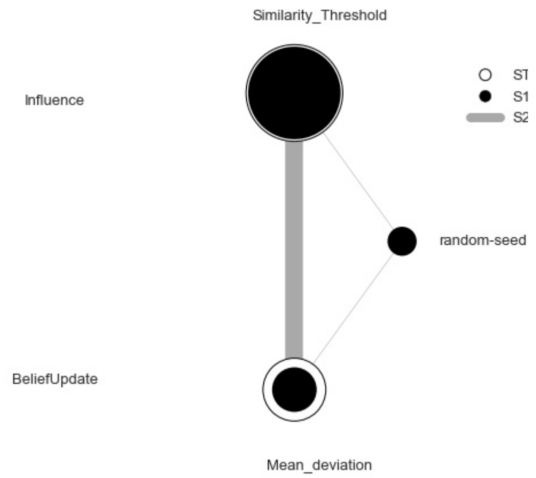

Figure 5.14: Sobol indices visualised form for all input variables with respect to the average size of reference groups for the ToM-model

5.4. CHAPTER SUMMARY

The aim of this chapter was to give insights on correctness of model properties and to provide information on model reliability. Through verification, validation and sensitivity analysis, there is sought for an answer to sub-question 3 of this research: *How can the realism of the agent-based model with a social influence component be evaluated?*

The simulation has been posed as verified in this chapter. However, the validation of the model is of more complex nature. This challenge mainly arises because of the complex nature of human actions (Sun & Müller, 2013). There is no 'gold standard' for models of social oriented models, since there is no golden standard for human behaviour. Therefore, the realism of agent-based models cannot be guaranteed at this moment. However, with a rise in popularity of agent-based models, study has been done to generate more standardised validation techniques for such models, in order to ascertain a certain level of realism.

What can be done in order to guarantee a certain level of correctness within this model, is highlighting the sensitivities within the model. From an multi-actor system perspective, for the full information transparency model, input variables proven to significantly contribute to output variance are the number of agents present in the model, the similarity threshold and the belief-points shifted at once during belief update. For the theory of mind model, the group size and similarity threshold also have proven to be influential concerning output variance, and the 'mean deviation' which indicated an agents' ToM-capacity is added to this list. These are the variables that need extra attention when parameter settings are determined. From an agent-based perspective, alongside the mentioned input variables, the number of students present in the model is also an input variable that has significant influence on agent behaviour. Therefore this variable is added to possible insightful input variables to include in further experiments.

6

COMPARISON OF MODELS

This chapter consists of three sections. In the first section, related work concerning the field of action adaption models is provided. By presenting this related work, findings from the two models created specially for this study can be put in context. Through related work there is searched for a standard in adaption of action models. These standards will shape the hypotheses used to compare the belief adaption models to the action adaption models.

The second section of this chapter is the first of the two sections providing results from the models in this chapter. This first section provides results from the model in it's non-varying initial parameter settings. First, these settings are presented. Subsequently, the results are presented, divided in a section on results of the full information transparency model, followed by results on the ToM-restricting information model. Both model present their results in three subsections; the share of influenced students, opinion dynamics and the transport mode choices. By this analysis a first hypotheses can be accepted or rejected.

The third section provides model output provided by simulations with varying parameter settings; the experiments. These parameter settings will be varied according to a hypotheses resulting from action adaption models, which is posed in the first section. This hypotheses concerns the social capital of agents, leading to the group size and the similarity threshold of the model to be varied with. This section is structured by first presenting the parameter settings of the experiment. Subsequently, the results for the full information transparency model are presented. Hereafter the results for similar experiments on the model with ToM-restricting information transparency is presented. Both outcome-sections are structured by first varying the group size and presenting the respective outcomes, followed by varying the similarity threshold and presenting the respective outcomes. Per outcome sections the implication towards the hypothesis are presented.

The aim of providing related work in section 1 is form an answer to sub question 2: *What is the typical macro behaviour of models where agents make predictions about their social-context based on the behaviour of others?,* will be presented.

The aim of section two is to provide an answer to sub-question 4: *How does belief-based social comparison affect social interaction and opinion-dynamics, compared to the conventional behaviour-based social comparison?* and sub question 5 *How does limited information-transparency between agents influence opinion dynamics and agent behaviour?*.

Lastly, through the experiments section, an answer to sub-question 6: *How do different levels of connectivity within the social network influence opinion dynamics and agent behaviour?* is presented.

6.1. RELATED WORK

Through this research, there is searched for the effects of social influence based on belief adaption. However, the independent effects of this specific angle on social reasoning is difficult to analyse due to the complex nature of social constructs as described in chapter 2.1.4. In order to still be able to analyse the effect of belief adaption on agent behaviour, this form of social comparison is set against action adaption, which serves as the benchmark for this study. Within models with action adaption, agents do not compare and adapt their private characteristics, but they compare and adjust their public characteristics. Two KPIs are chosen to represent the extend to which both model versions are similar or different, i.e.:

1. Opinion dynamics
2. Transport mode choices

For the comparison on these KPIs, related work within different fields of research need to be addressed. This, because for studies on transport mode decision with social influence based on behaviour, opinions are not taken into account. For studies on shifting opinions on transport modes by social comparison on the basis of beliefs, the focus lies on the shift in beliefs whereas the decision for a transport mode is not mentioned. Therefore, this section will first address related work in the field of opinion dynamics, followed by related work on transport mode choices.

OPINION DYNAMICS

In 1964, Abelson stated that in situations where actors would imitate each others behaviour, inevitably there is moved towards group consensus. However, since then researchers have opposed to this statement, as social influence by itself does not create uniformity of opinion and social influence does not lead to convergence of opinions towards the mean of the opinion space, but often results in polarisation (Nowak et al., 1990). Also Axelrod (1997) posed an important question letting people doubt Abelson's statement:

> "If people tend to become more alike in their beliefs, attitudes, and behaviour when they interact, why do not all such differences eventually disappear?"

By posing this question, Axelrod highlighted the possibilities of other opinion dynamics, such as non-centralised clustering. Others from this period in time supported polarisation being a possible result of social interaction. such as Myers & Lamm (1976) and later

Nowak et al. (1990). Sunstein (2002) takes this a step further, and states that polarisation within the opinion space is the most robust pattern found in decision making influence by social networks. By polarisation, there is not necessarily meant that all opinions shift towards the poles, but it indicates that opinions shift within a group, in such manner that far apart clusters of co-oriented agents and opinions arise (Sunstein, 2002). Most of the time, group members do not move towards the average of opinions within the group, but they tend to coalesce towards a more extreme position (Sunstein, 2002). The explanation for these group-opinion dynamics can be found within the social comparison process (Sunstein, 2002). The urge for social acceptance causes agents to move their opinions towards those of group-members they feel or want to be close to, in order to be perceived as how they perceive those other group members (Sunstein, 2002).

Although clustering is an often used way to predict opinion dynamics within a heterogeneous group, social systems, their opinion formation and social learning remain a complex research field, because of its person-, domain- and case specificity and because of its sensitivity; nuance-differences can steer individuals or groups into a different direction (Acemoglu & Ozdaglar, 2011). However, for the opinion dynamics within the heterogeneous group in the simulation on transport mode decisions, from this back ground information the following hypothesis emerges:
Agents will shift their beliefs over time in order to form clusters of agents with the same beliefs

Lastly, Urbig et al. (2008 have performed research on the topic of influence of social networks on opinion dynamics. Their finding is, that the higher the connectivity within a network, the more consensus can be found. This statement will be held as an hypothesis to be tested within this chapter's experiments section. In Chapter 5, there has been pointed out that elements from the social context do have a significant influence on the behaviour of the model. Two of these influential input variables are the group size and the similarity threshold of agents. There will be varied with these input variables in order to test the hypotheses resulting from Urbig et al.'s work.

6

TRANSPORT MODE CHOICES - TYPICAL MACRO BEHAVIOUR

Another part of differences between belief adaption and action adaption models will be translated into the choice of transport mode. In order to put the respective output of the model in context, more information on previous research in this field is presented in this section.

Research on transport mode decision-making, steered by social comparison is executed by Dugundji & Gulyás 2008. In their model, the behaviour of heterogeneous agents which influence each other based on their socioeconomic situation and geographical properties. Note that because of this and other aspects that will be described later in this paragraph, a different social interaction process is modelled. This model not only lets agents compare their behaviour, but also designs heterogeneous agents using different concepts and creates different rules for social interaction. However, unfortunately there is no study with exactly the same simulation environment. Therefore, Dugundji & Gulyás)'s study which has a decision model on transport mode choices influenced by social interaction, is good enough to enables the comparison of behaviour of both models, while taking into account their differences.

The resulst of Dugundji & Gulyás's (2008) model are presented in figure 6.1.

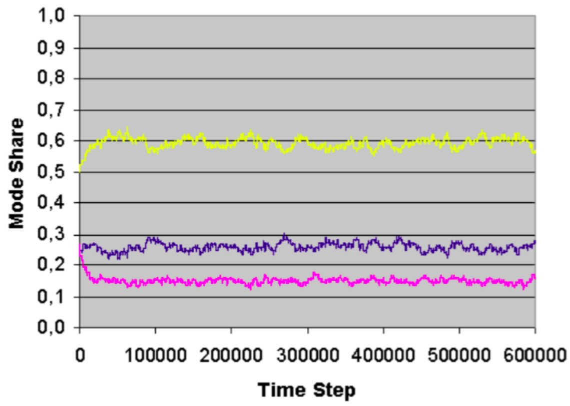

Figure 6.1: Mode shares over time as a result of social influence. Source: (Dugundji & Gulyás, 2008).

For the comparison in behaviour, the exact shares for specific transport modes are not the topic of interest. The focus will be put on the dynamics of decisions for specific modes over ticks. With this in mind, the conclusion that can be taken from this figure is that in this reference study mode shares stay relatively constant over time despite social interaction between heterogeneous agents.

6

From this conclusion, the following hypothesis for the behaviour concerning mode shares is derived:

After a small shift at the beginning of the simulation, mode shares will remain relatively constant.

As aforementioned in this section, differences between the two studies pose a barrier concerning the comparison of behaviour. Besides the described reference point for social influence, other differences are that the reference model is a nested logit model with agents making decisions based on their utility maximisation, as opposed to the model within this thesis having deliberately stepped away from the trend of using utility maximisation to substantiate decision-making processes.

The aim of this section was to form an answer to the sub research question: "What is the typical behaviour of models where agents make predictions about their social-context based on the behaviour of others?". Through exposing the frame of reference where this study fits into, three hypotheses concerning expected behaviour have arisen:

1. *H1*: Concerning the opinion dynamics related behaviour, clustering of opinions appears to a higher degree as the course of the simulation progresses. (Fixed parameters)

2. *H2*: Concerning mode share distributions, after reaching an equilibrium in the first stage of the simulation, the shares will remain stable. (Fixed parameters)

3. *H3*: Concerning the opinion dynamics, the higher the connectivity within a network, the more consensus can be found. (Experiment with varying parameters)

6.2. MODEL OUTCOMES UNDER FIXED PARAMETERS

The results of the simulation study with all its initial parameter settings and assumptions is analysed. In this section, all parameters are held constant to their initial settings. This analysis will concern the outcomes that reflect the trivial summations of rules as imposed on the individual level, but some outcomes may present emergent properties that are not directly traceable from properties on the individual level. By analysing these outputs, the hypotheses concerning fixed parameters as formulated in the related work section can be tested. For completeness, this concerns the following hypotheses:

1. *H1*: Concerning the opinion dynamics related behaviour, clustering of opinions appears to a higher degree as the course of the simulation progresses.

2. *H2*: Concerning mode share distributions, after reaching an equilibrium in the first stage of the simulation, the shares will remain stable.

For both the analysis of the ToM-included model and the model with full information transparency, the same hypotheses will be tested.

The aim of this section is to answer sub question 4 *"How does belief-based social comparison affect social interaction and opinion-dynamics, compared to the behaviour-based social comparison?"* and sub question 5 *How does limited information-transparency between agents influence opinion dynamics and agent behaviour?* can be given.

This section begins with a description of the simulation setup. Subsequently the results of the model with full information transparency are presented, including the share of socially influenced agents, their opinion dynamics and the mode share distribution. Hereafter, the same aspects are discussed for the model with ToM-restricted information on beliefs, values and travel satisfaction of other agents. Their differences will be identified and hypotheses will be confirmed or rejected.

6

6.2.1. SIMULATION SETUP

In this section the conditions under which the model is ran in its 'basic form' are presented.

PARAMETERSETTING

The following settings have been used to explore the base case scenario. A number between brackets ([**n**]) behind an initial parameter setting, refers to a further explanation of this parameter choice indicated by the respective number in Appendix 9.5.

- Group-size (20 students) [**17**]

- Share of bike-owners (75%) [**18**]

- Share of car-owners (10%) [**19**]

- Similarity threshold (7) [**20**]
  Similarity threshold means the maximum amount of points indicating value-importance that agents can think differently on and still see each other as co-oriented peers.

- Increment of influence-strength of relations between agents **[15]**
  Once agents can build a relation because of their perceived similarities, the degree to which the influence-strength of their relation increases depends on their prosociality. Table 6.1 presents the initial values for these influence-strength increments.

		Prosocial of self		
		0	**1**	**2**
Prosocial of other	**0**	0	0	0
	1	0	0.25	0.5
	2	0	0.5	1

Table 6.1: Influence-strength increment subjected to prosocialness

- Amount of belief-points agents shift towards their co-oriented peers (relation-strength < 25 : 0.005, relation-strength > 25 : 0.01, relation-strength > 50 : 0.05) [**16**].
- Prosociality (normal distribution with mean = 0.48 and sd = 0.42) [**8**]
- Beliefs about value-activity relations
  These initial beliefs depend on the travel type of a student and can be found in appendix 9.5. They are not completely determined by the travel type, as variations within certain boundaries give space for agents to find agents of another type co-oriented to themselves.
- Importance attributed to values
  Just as with beliefs, the importance attached to values is agent specific put is given direction by the travel type of a student. Exact values given to this variable can be found in appendix 9.5.

It is important to note that all output generated by the model for this reference run are a result of these parameter settings and the assumptions as can be found in appendix A. As is stated in Chapter 5, this model is subjected to a variety of uncertainty and a challenged validation. Therefore it is important to keep in mind that the outcomes of the model are an artefact of the model rather than universal results.

EVALUATED OUTPUT VARIABLES, RUN LENGTH AND REPLICATIONS

The run length chosen for this study is 1500 ticks. This amount of ticks gives agents the time to adjust their beliefs to a new equilibrium in their new social environment. Note that a tick does not represent a time-related concept. During every tick, agents make up their mind about what others belief and prefer and about their own preferences. However, saying that each tick represents one decision would also restrict the model in an unnecessary manner, as one does not necessarily have to execute the chosen action in order to evaluate the possibilities and preferences given to these options of oneself and others. Therefore, in this study letting agents interact over more than one tick is a means

to the end of capturing the dynamic aspects of the system. This way, there can be analysed how the system reaches a new equilibrium under specific parameter settings and assumptions. The simulation has been set to 100 replications, and because of the specific value-activity combinations that have to be made for analysis purposes, this results in 2100 runs.
The KPIs that capture the differences in behaviour of the system under specific parameter settings and assumptions are as follows:

- Share of socially influenced students
- Beliefs (per activity - value combination)
- Change of beliefs over time (per activity - value combination)
- Group size of co-oriented peers
- Choice of transport mode

6.2.2. MODEL OUTPUT - SIMULATION WITH FULL SOCIAL-INFORMATION TRANSPARENCY

Firstly, the results for the model where agents have full insight in the private characteristics: values, beliefs and travel satisfaction of others. The hypotheses concerning opinion dynamics and travel mode choice is tested within this section. In order to be able to put the respective results in context, first the average share of students involved in the social interaction in the model and their belief adjustments over time are discussed.

SHARE OF SOCIALLY INFLUENCED STUDENTS

Through social interaction, agents adapt their beliefs and can be described as 'socially influenced agents'. Not all agents in the simulation will be socially influenced, because of two reasons. First of all, some agents do not find any of the other agents' values similar enough compared to their own values and consequently are not willing to take preferences of these agents into account when making a decision. A second reason for agents not interacting with any other agent can be the prosociality of an agent. Low prosociality can result in an agent not wanting to adjust their beliefs towards others leading to a socially-isolated situation. The frequency with which a certain share of socially influenced students is reached within the performed 2100 runs is presented in figure 6.2.
As can be seen in figure 6.2, most of the social interaction possibilities (in most of the ticks during most of the simulation runs), result in an average of 75% of the students being socially influenced, with a standard deviation of 12 percent-points. The mean is represented by the green striped line in figure 6.2. This means, that within this reference case of 20 students, most of the time around 15 students are socially influenced, leaving 5 students on average not adjusting their beliefs through social comparison. An example of a social network as appears in one of the runs of the model, is presented in figure 6.3. This social network shows that when agent A finds itself similar to agent B, and agent B finds itself similar to agent C, agent A does **not** necessarily need to also find itself similar to agent C. This means that the social network present in the simulation is incomplete.

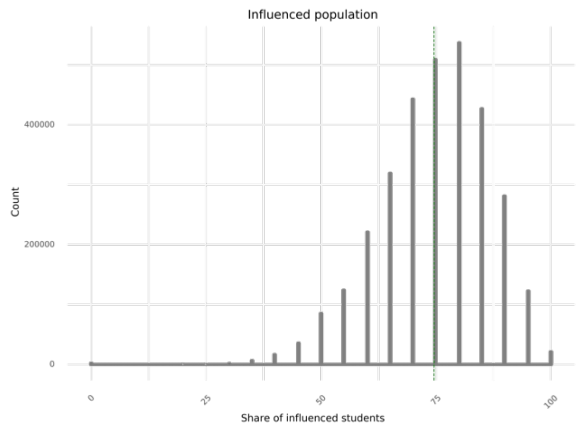

Figure 6.2: Histogram of number of socially influenced students

Furthermore, 6.3 also shows that the relations between agents do arise often but solely between agents of the same travel type.

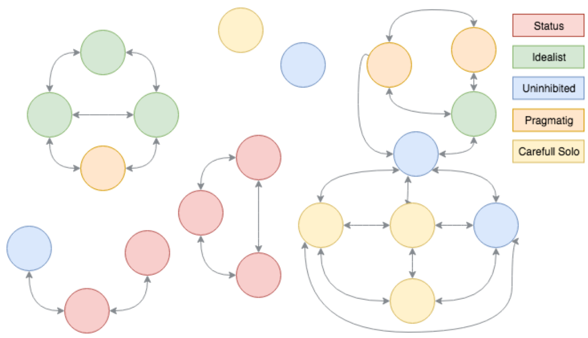

Figure 6.3: Example of a possible social network, as appeared in one of the simulation runs

Although not all students are socially influenced, their beliefs also change over time as a result of personal evaluation of travel satisfaction. As a result, beliefs keep changing over time. Figure 6.4 displays this change of beliefs of agents. The 'change of beliefs' variable is an indicator for the average amount of points students adjust their beliefs with every evaluation moment in the model. It gives an indication of the increase or decrease in belief-adjustment per agent compared to the previous tick. Note that the change in belief-points variable is taken as to be a mean of the change in beliefs over all value-activity combinations and over all replications of the model. The standard deviation of the mean change of beliefs per evaluation moment is 0.016. As can be seen in figure 6.4, in the beginning of the simulation this change in beliefs per tick can rise up to almost 0.07 points per agent on average. As the simulation progresses, this change in beliefs per evaluation moment decreases. An explanation for higher belief-adaptions in the beginning of the simulation might lie in the fact that agents are aware of who they consider to be co-oriented in relation to themselves, and they still have a relatively large difference between the beliefs of these co-oriented peers and their own. Therefore, for more mode-value combinations, belief-adjustments will be made. Subsequently, the attenuation of this belief-adaption can be explained by agents having already adapted their beliefs towards the beliefs of their co-oriented peers, leading to less belief adaption through social influence. Moreover, when beliefs have reached either side of the poles of the belief space, strengthening beliefs in the direction of the poles is no longer possible. This can also result in a stagnation in belief adaption.

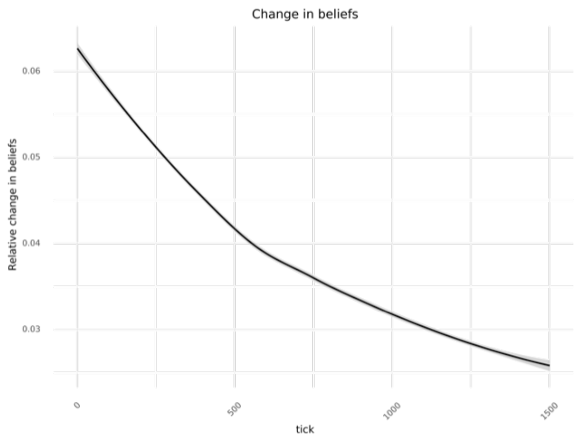

Figure 6.4: The average change of beliefs of agents per tick

OPINION DYNAMICS

The next step is analysing what the result of these social and personal evaluations and belief adaptions are over evaluation moments. In figure 6.5, the belief dynamics for the value 'fun' and transport mode 'car' are displayed. As can be seen in the figure, part of the agents increases their beliefs of the relation between car and fun, meaning that they are more convinced of the car being a mode of transport that brings fun with travel.

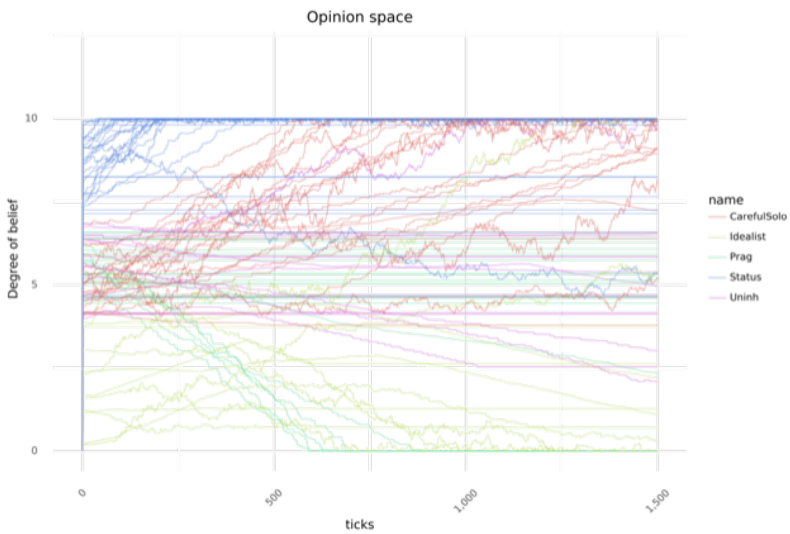

Figure 6.5: The average change of beliefs of agents per tick for the belief in a connection between fun and the use of the car

Another part of the agents decreases their beliefs on the relation between fun and car usage, meaning that they are less convinced that the use of the car can bring fun into their transport experience. A third behaviour shown within figure 6.5 is brought by zealots within the model; agents that do not change their beliefs over time. It rarely happens that agents do shift their beliefs, but are not drawn to the poles of the belief space. Furthermore, the figure shows the behaviour of different travel types by distinguish the types by colour. As can be seen, the travel types seem to cluster to some extend. There are also cases where students from the same type do not adjust their beliefs into the same direction as the travel types of their type.

A few things can be noted from observing figure 6.5. First of all, because there is a relatively large chance that students from the same travel type consider themselves as to be co-oriented, there is a larger chance that these students will develop their beliefs in the same direction through social influence. However, for some types this change of belief adaption is bigger than for other types. This is due to two components: (1) the strength of student values and initial beliefs and (2) the prosocialness of students. Zooming in on the first component, an agent with high importance attained to fun will more often make a decision with the aim of satisfying its fun level. This occurrence of a more frequent belief update when a value is found more important, can be derived from figure 6.6. As can be seen in figure 6.6, agents with a low importance attached to the value fun (represented by orange beliefs), more often turn into zealots. Agents that find fun important as a value (represented by blue beliefs), tend to choose a transport mode while wanting to satisfy their fun-level more often, resulting in an evaluation on how that decision turned out in terms of value-satisfaction and thus resulting in a belief-shift.

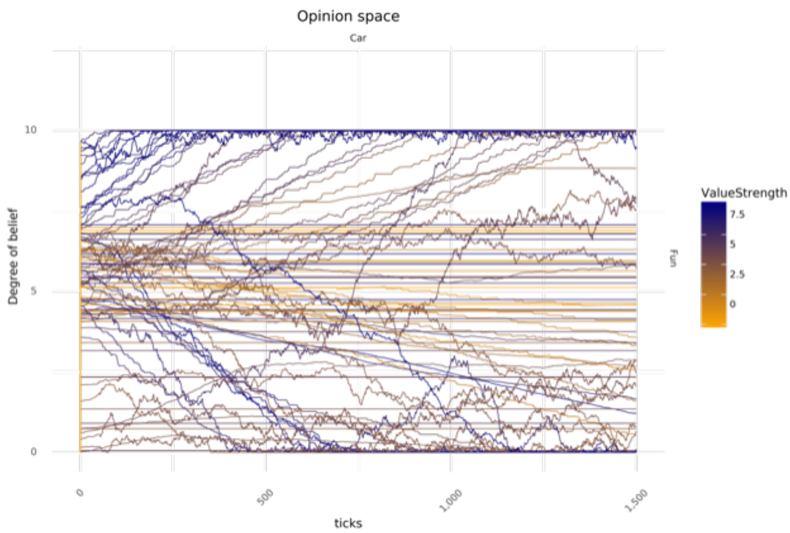

Figure 6.6: The average change of beliefs of agents per tick for the belief in a connection between fun and the use of the car, with color palette adjusted to the importance given to the value ’Fun’

After such a decision-moment, the chosen transport mode and its performance in satisfying the fun level is evaluated. As appears from figure 6.5, agents that undergo this belief-update process, often conclude that the car did satisfy their urge for fun in a positive manner, leading to an increase in this belief. This evaluation depends on their current beliefs; an already strong connection will support this decision, while a disbelief of the car being a means to the end of satisfying fun levels will result in disappointed when this transport mode is (probably by a lack of other options) chosen. Thus, the belief-value combination results in an increase or decrease of personal evaluation if this transport mode is chosen. Then, with relatively similar beliefs and values, the amount of times a value-mode combination is evaluated (i.e., the frequency with which the beliefs on this relation are updated) and the direction of the shift in beliefs resulting from this update process is more similar. As an illustration for this importance of values and initial beliefs, the beliefs on the relation between environmental friendliness and taking the bus is presented in figure 6.7. When this figure is compared to figure 6.5, one can see that more stable beliefs occur from zealots and the shift in beliefs does not show clusters of the same travel type. There are more stable beliefs, because less agents will implement the action of taking the bus as a means to satisfying their environmental values, preventing this belief to be subjected to personal evaluation. The reason for not choosing the bus can be found in the fact that most of the agents have a bike, which is considered to be more environmental friendly by most agents. Then, because of the fact that the initial beliefs are less divergent than for the car - fun relation (the bus is considered to be mediocre for the environment, as the bike is also an option but it is considered better than the car), the belief dynamics when lowering the beliefs about this transport mode value combination seem to be more similar for all agents of all types. However, it is important to note that this does not mean that these agents of different value types are influencing each other now within this belief relation. Social interaction is still determined by the agent-differences over **all** value-mode combinations. The resemblance of behaviour over all travel types is solely an artefact of the initial beliefs and values of agents in this case.

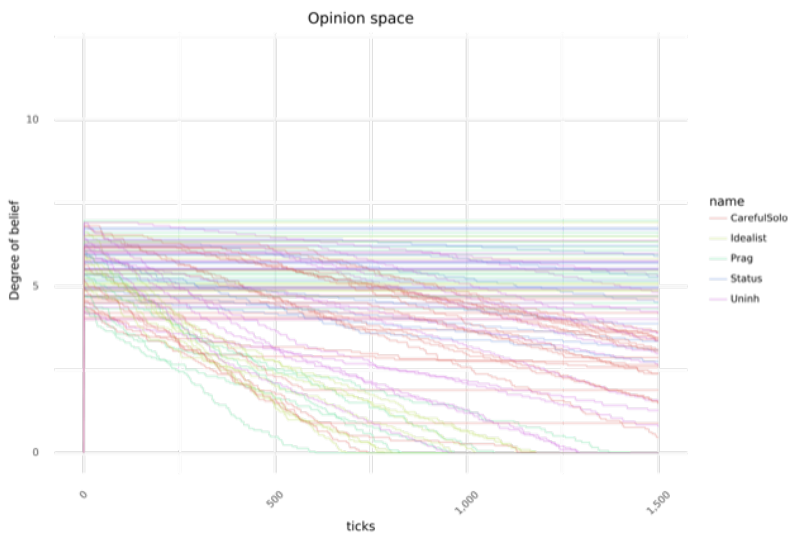

Figure 6.7: The average change of beliefs of agents per tick for the belief in a connection between environmental friendliness and taking the bus

Besides these values and initial beliefs, the prosocial characteristics of an agents are also elements which influence agent beliefs over time. This is because prosocial agents are more willing to interact and adjust their beliefs to others than agents with a low prosociality level. Agents with low prosociality, are not interacting with other agents and thus only adjust their beliefs according to their personal evaluation when a certain transport mode has been chosen for the satisfaction of a value. Some travel types have a larger chance of being prosocial than other travel types (see appendix C for more information). Because of this, some travel types will have a larger chance of having stable beliefs because of a lack of social influence.

In short, the macro behaviour presented in figure 6.5 shows an increase of clustering as the simulation progresses. As is described in section 6.1, polarisation does not necessarily need to result into an opinion space with only two clusters of opinions on both sides of the opinion poles, some opinions may stay unaffected or affected in to a smaller degree. This is the case for the results for the reference run, leading to the opinion dynamics to be best described as a resemblance of polarisation. To be able to give more

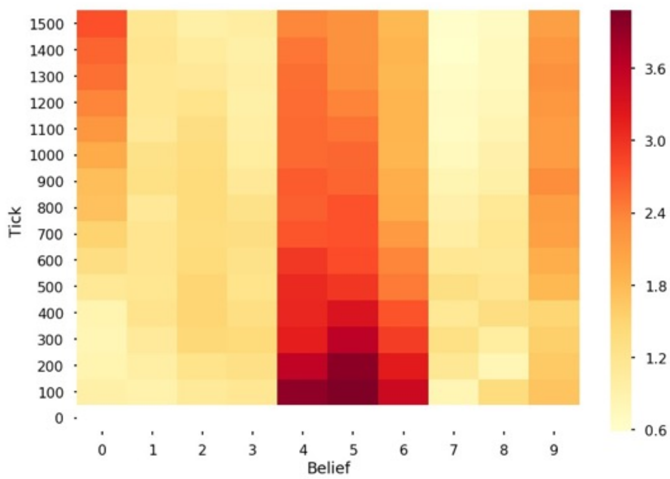

Figure 6.8: Heat map representing the number of students with a specific belief for the car - fun relation over evaluation moments

insight on the validity of the hypothesis of interest in this section, figure 6.8 provides a heat map of beliefs over time. In this heat map there is shown how the average number of agents having a certain belief allocated to a transport mode - value combination changes over evaluation moments. The darker the square on the heat map, the higher the number of students with this belief at this moment in the simulation. For the calculation of the average number of students with a certain belief, the mean of the size of reference groups over 2100 runs has been used. This mean is accompanied by a standard deviation of 0.37. This average size of reference groups gives a good representation of the belief-dynamics within the opinion space. This, because small reference group sizes means that the student-beliefs are spread more over the complete belief space. This divergence has a scattered heat map as a result. When the average reference group size on a specific belief-point is large, this means that clustering has appeared and other points in the belief-space most probably will have a decreased number of students with this certain belief. As can be seen in figure 6.8, with more evaluation moments having past, the beliefs of students seam less spread over the belief space, but more clustered at three specific points; both ends of the belief space and at the centre. Few students beliefs end somewhere different than at these points. This confirms the findings from figure 6.5; agents beliefs either remain relatively unaffected and stay at their initial position within the opinion space, or agents shift their beliefs until they have reached one of the poles of the opinion space. With this finding, the hypothesis of clustering of opinions appearing as the course of the simulation progresses (*H1*), is accepted with running the model in its initial parameter settings and under all assumptions as specified in appendix A.

THE TRANSPORT MODE CHOICE

The described shift in beliefs, will lead to different outcomes with the trade-off between the transport mode options. A decrease in belief in a certain transport mode - value relation, will lead to an agent not choosing this transport mode anymore when trying to satisfy this value. The share of transport modes being chosen over evaluation moments are shown in figure 6.9.

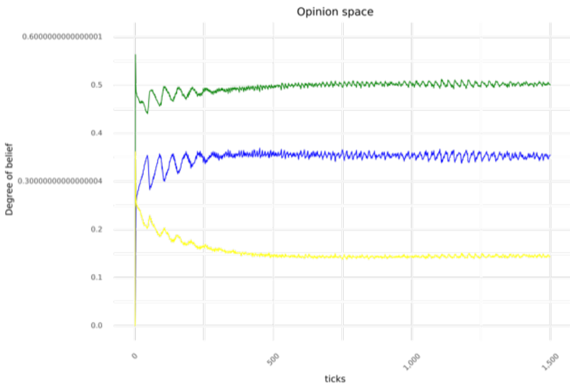

Figure 6.9: Share of transport modes implemented, over evaluation moments

As can be seen in figure 6.9, in the beginning of the simulation the share of chosen transport modes fluctuate more than later in the simulation. A reason for this, can be the bigger shift in beliefs that is taking place in this starting point, as was concluded from 6.4. After a while, agents will 'settle down' with concern to their beliefs, also leading to a more constant behaviour when having to choose their transport mode of preference. Thus, hypothesis *H2* is accepted for the model with full information transparency.

6.2.3. MODEL OUTPUT - SIMULATION WITH BOUNDED TRANSPARENCY THROUGH THEORY OF MIND-CAPABILITIES

This section describes the similarities and differences in model-outcomes when ToM-capabilities restrict the capacity of agents to predict others' values, opinion dynamics and travel mode choice. Similar to the previous section, this section first describes the share of socially influenced students, followed by the opinion dynamics and mode share resulting from this model. By analysing these components, the validity of the hypotheses under ToM-conditions can be examined.

THEORY OF MIND RELATED INITIAL PARAMETER SETTINGS

Besides the initial parameter settings as described in section 6.2.1, this model contains of additional variables and thus requires additional initial parameter settings.

- **Prosociality - ToM relation**
  The prosocialness of an agent is translated into a specific theory of mind capability level which results into a specific deviation when prediction others' values, beliefs and transport satisfaction-level **[9]**. This is represented in the model by equation 4.2 and the initial parameter settings for the different theory of mind levels of agents regarding to the extra mean and standard deviation values are presented in table 6.2.

	Prosocialness (x)				
	$0 < x \leq 0.2$	$0.2 < x \leq 0.4$	$0.4 < x \leq 0.6$	$0.6 < x \leq 0.8$	$0.8 < x \leq 1.0$
ToM-level	1	2	3	4	5
Extra-mean deviation	0.8	0.6	0.4	0.2	0
Standard deviation	1.5	1.2	0.9	0.6	0.3

Table 6.2: Theory of mind related deviations as a result of prosocialness-levels

SHARE OF SOCIALLY INFLUENCED STUDENTS

Just as with the full information transparency, agents have the ability to influence each other through social comparison. However, the information used as comparison material in the ToM-model is not as clean it is from the non ToM-restricted model. Therefore, agents might be willing to adjust their belief towards beliefs of agents within their reference group, but because of their conjecture about agents' that can be wrong, beliefs might not end up with a more similar belief after this adjustment. The share of socially influenced agents is represented by figure 6.10. Thus, when restricted information transparency is introduced to the simulation, a considerably lower share of students will be subjected to social influence. A reason for this might be found in (mis)calculations of students concerning the state of others, withholding them to consider themselves as being co-oriented peers.

Furthermore, the degree of the average belief adjustment as a result of this social influence also differs from the results in the previous section. Figure 6.11 shows that at its highest, the points shifted in beliefs per evaluation moment is 0.05 points and at the lowest part this concerns 0.005 points. This means that for the belief adjustment in the ToM-model, the highest increase in belief adjustment resembles the lowest value of belief adjustment per evaluation moment in the full information transparency model. A reason for this might be found in the possible (mis)interpretations of agents on others private characteristics, which withholds agents from moving their beliefs to the same direction as other agents *actual* beliefs. This leads to a situation where agents lose sight of each other and do not consider themselves being co-oriented anymore. Then, reference groups remain smaller, and thus the beliefs of agents would be steered by fewer other agents, resulting in a smaller belief shift per evaluation moment. In the following paragraph there will be analysed if this finding is supported by accompanying results.

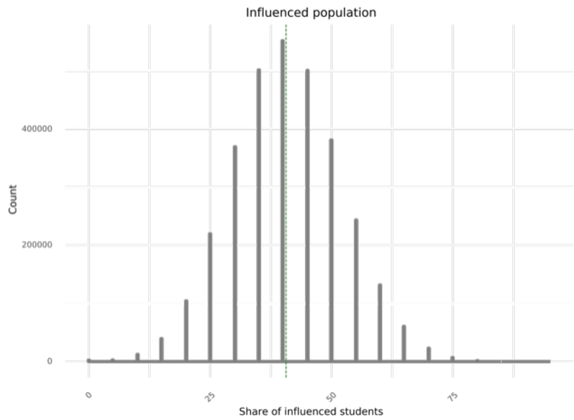

Figure 6.10: The share of socially influenced agents under ToM-restricted insight on other agents' state

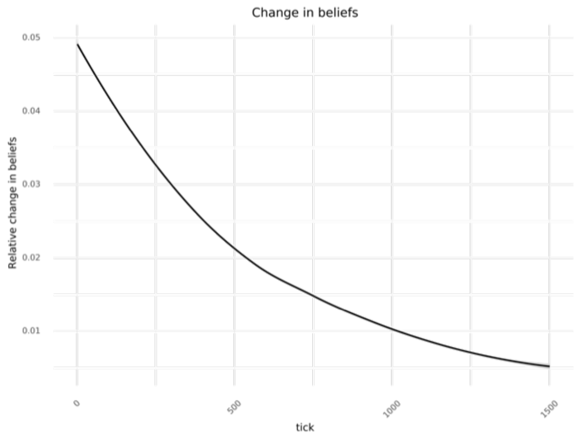

Figure 6.11: The average change in beliefs in points per evaluation moment for the ToM-model

6

OPINION DYNAMICS FOR THE TOM-MODEL

Likewise, for the ToM-model beliefs of agents over evaluation moments are analysed. An example of belief dynamics is shown in figure 6.12. This figure concerns the beliefs on the relation between compatibility and the car. As can be seen, the status oriented agents seem to quickly 'team up' and adjust their beliefs in a positive direction. But, putting this aside, there can be seen distinct differences from this figure and the opinion dynamics as presented in figure 6.5. A more diffuse spread of beliefs seems to be the result at the end of the simulation.

When we accompany this plot with a heat map of the beliefs for this value - transport mode combination (figure 6.13, similarities can be seen when compared to figure 6.8, but there is one difference that stands out. Concerning the similarities, the opinion space contains more clusters as the simulation progresses, with some agents jointly moving their belief to the lower belief-space pole. However, The space between this pole and the centre as well contains a significant fraction of all beliefs (and thus remains a darker shade of orange). This means that the belief space still is more scattered than in the model with full information transparency. Thus, hypothesis *H1* does not apply in the same degree to the ToM-model. However, hypothesis *H1* cannot be rejected, as cluster-

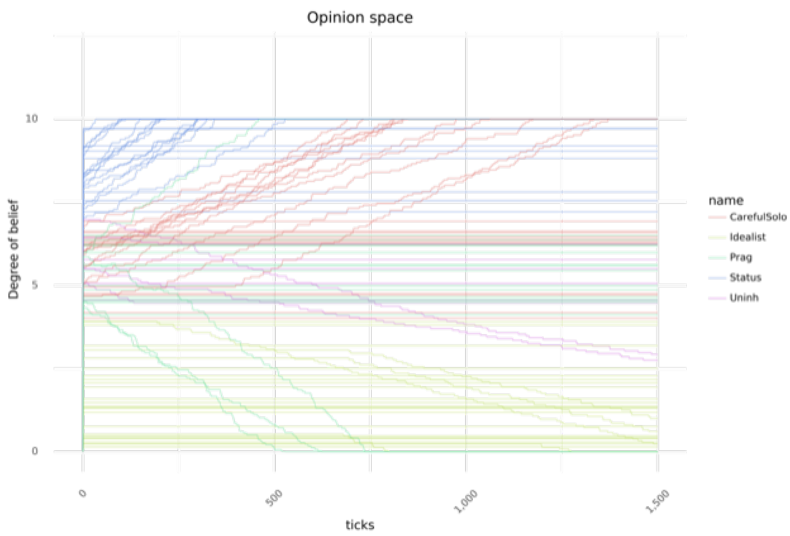

Figure 6.12: The average change of beliefs of agents per tick for the belief in a connection between comfort and the use of the car

ing does appear in a higher degree as the course of the simulation progresses. Therefore, hypothesis *H1* of increasing clustering over the course of the simulation is accepted, but less convincingly than for the model with full information transparency.

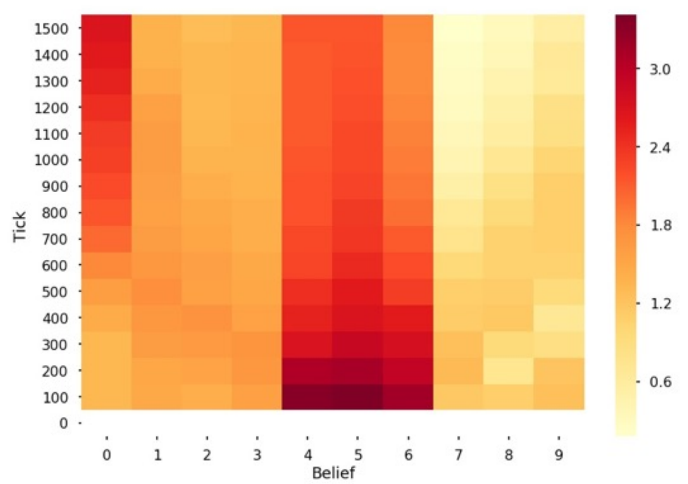

Figure 6.13: Heat map representing the number of students with a specific belief for the car - fun relation over evaluation moments, for the Tom-model

TRANSPORT MODE CHOICES FOR THE TOM-MODEL

Now that the similarities and differences within opinion dynamics between both models are made clear, the next step is to display the effects of these dynamics on the mode choices of agents. The average mode shares during the simulation are presented in figure 6.14. There can be concluded from figure 6.14 that just as for the model with full information transparency, mode shares fluctuate in the beginning of the simulation and hereafter reach a new equilibrium and stabilise. Through this finding, hypothesis *H2* can also be accepted for the model with ToM-restricting information transparency.

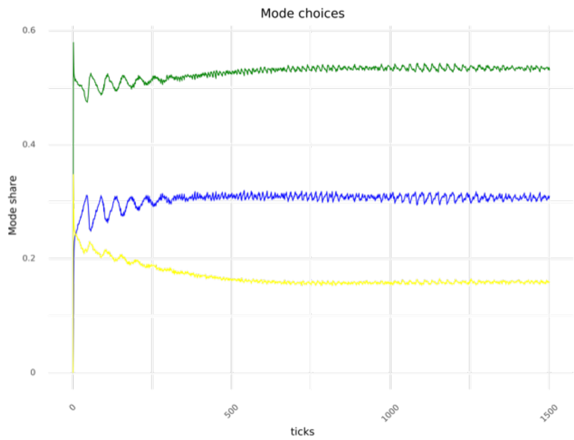

Figure 6.14: Share of transport modes being implemented over evaluation moments - with ToM influence

6.3. EXPERIMENTS - VARYING PARAMETERS

This section describes the relation between the social capital in the simulation model and the opinion dynamics and transport mode choices provided by the model.

6.3.1. EXPERIMENT SETUP

As mentioned in the introduction, for examining the influence of agents social capital on their opinion dynamics, the input variables group-size and the similarity threshold will be varied. The group-size will be varied from 5 to 40 agents in steps of 5. The similarity threshold will be varied with from 5 to 21 value-points in steps of 2. For each experiment with a specific parameter value, 100 replication will be generated to be able to compute average values. The effect of different group-sizes and similarity threshold will be shown for the the opinion dynamics within the beliefs on the relationship between the mode 'car' and the value 'fun'.

6.3.2. EXPERIMENT OUTPUT - MODEL WITH FULL INFORMATION TRANSPARENCY

In order to test the hypothesis (*H3* that results from related work, the network density will be affected by increasing both the group size and the similarity threshold. A higher similarity threshold leads to more agents concerning themselves to be similar to others and thus establishing a social relation. A larger group of students subsequently leads to more agents subjected to comparison, leading to agents being able to include more others to their reference group and hereby increasing their social capital. Note that by group size, there is meant the size of the complete group of students, not the size of reference groups of students.

First of all, the influence of the social capital of agents on opinion dynamics is analysed for the situation where agents have full insight on the states of others. As was concluded from the sensitivity analysis, both the number of students and the similarity threshold have appeared to be influential for the value of all identified KPIs (size of reference group, average change in beliefs and share of influenced students). In this section the exact result of an increase in these input variables related to the social capital of agents will be analysed.

THE GROUP SIZE

A larger group of students, means that agents have the possibility to connect to more other agents and thus expand their social network. The initial setting of group size in the model is set to be 20. As the hypothesis within this chapter states, expected is that a larger group of students will lead to opinion-dynamics presenting more consensus.

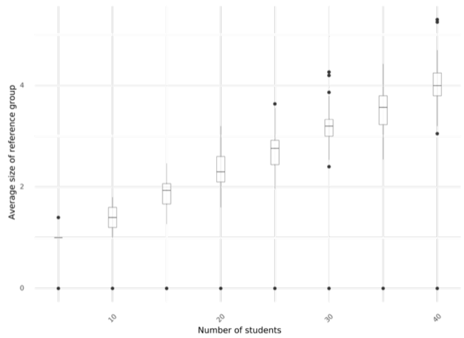

Figure 6.15: The mean change in beliefs for different group sizes under full information transparency

Figure 6.15 presents the average sizes of reference groups, as an indicator of the connectivity within the agent-network. As can be seen from the box plot, the more students present in the simulation, the larger the reference groups of agents and thus, the more agents established a connection and consider themselves as co-orienteds. The outliers on the zero line of the box plot represent the students who are not socially influenced throughout the simulation. Moreover, with a larger reference group and thus more agents to compare oneself to, a different change in beliefs through social influence would be expected.

When the opinion dynamics under different number of students present in the simulation is inspected, social interaction leeds to different behaviour of beliefs over ticks. This difference can be seen within the opinion space. Figure 6.16 presents the belief space for a mode-value combination with 5, 20 and 40 students present in the simulation. For a complete overview of the affect of all different group sizes on opinion dynamics, appendix E can be consulted. As can be seen from figure 6.16, more beliefs are shifting over time. A conclusion from this can be, that the larger the group of students in the simulation model, under the described parameter settings and assumptions, more agents are socially influenced and shift their beliefs accordingly.

Figure 6.17 shows that this increase in shifting opinions, results in higher numbers of students with the same opinion as the simulation progresses (see appendix E for full overview). For this heat plot, the intensity of the colour red is an indication for the per-

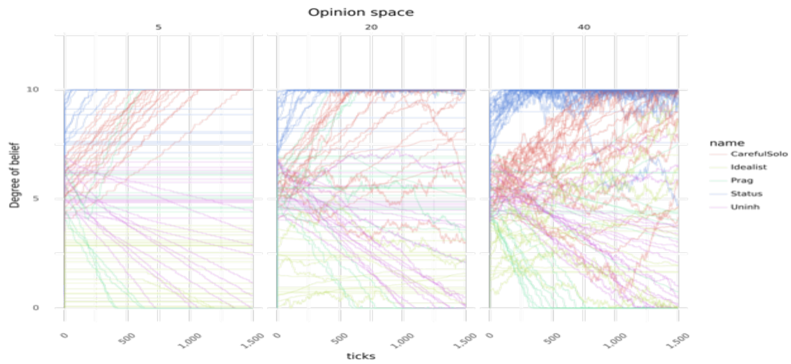

Figure 6.16: Opinion dynamics for different group sizes, under full information transparency

centage of students on this point in the belief space. By working with percentages for heat plots with varying group sizes, the affect of more students leading to higher values is evened out. Furthermore, figure 6.17 shows that convergence of beliefs finds place on both poles of the belief space. This means, that clustering increases as the number of students present in the simulation increases. Because of polarisation towards both poles of the belief space, there is no full consensus, but partial consensus. With the presented findings on the effect of group size on opinion dynamics, one can state that the hypothesis of a higher connectivity within the social network leading to more consensus, is proven to be valid for the simulation model with full transparency with the assumptions as stated in appendix A and under its initial parameter setting with solely the number of students present varying.

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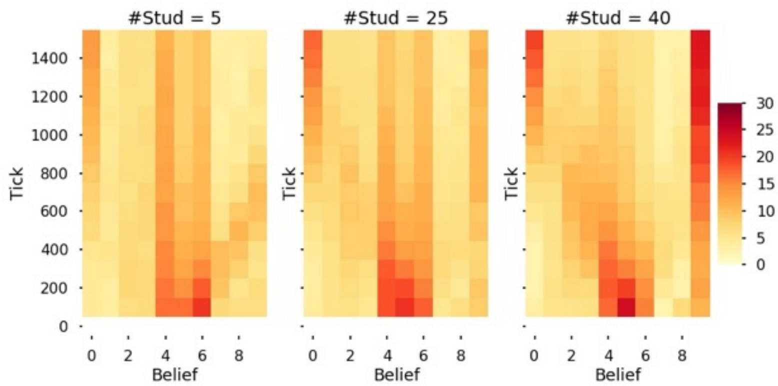

Figure 6.17: Heat map of the number of students with specific beliefs over the simulation with full information transparency, for varying group size

SIMILARITY THRESHOLD

The second input variable resembling the connectivity of the social network, is the similarity threshold. The higher the similarity threshold, the higher the maximum of differences in value-points agents can have in order to consider themselves co-oriented. In short; the higher the similarity threshold, the quicker agents find themselves likeminded. As a result, reference groups increase which has an affect on the social interaction (see appendix E for supporting figures). Figure 6.18 displays the opinion dynamics under differing similarity thresholds (e.i., a similarity threshold of 5, 13 and 19). As can be seen from this figure, a higher similarity threshold leads to more fluctuation of beliefs of agents over ticks.

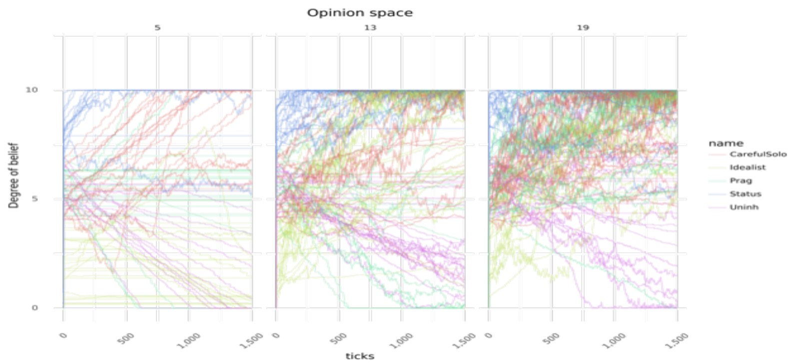

Figure 6.18: Opinion dynamics for different similarity thresholds, under full information transparency

When the direction of these fluctuations in beliefs is analysed, figure 6.19 shows a trend of beliefs accumulating on one pole of the belief space as the similarity threshold increases. This means, that a higher similarity threshold leads to an accumulation of beliefs. When compared to figure 6.17, even more consensus can be read from the figure, as all opinions shift to one point in the belief space, whereas for the increase in group size under full information transparency, two strong 'belief-camps' are represented within the belief space.

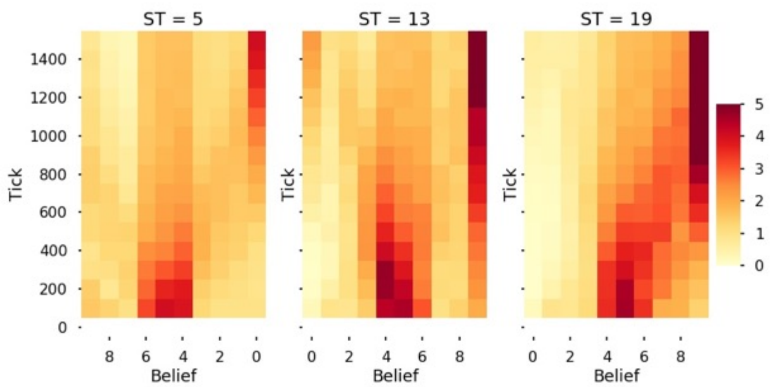

Figure 6.19: Heat map of the number of students with specific beliefs over the simulation with full information transparency, for varying similarity threshold

Summing up the findings of this subsection, one can conclude that through an increase in the similarity threshold, under full information transparency and all other assumptions as stated in appendix A, the consensus within the social network increases and thus within this subsection the hypothesis is accepted.

With both an increase in group size and the similarity threshold leading to more consensus, there can be stated that a higher connectivity of the social network leads to more consensus. Thus, hypothesis *H3* can be accepted for the model with full information transparency.

6.3.3. EXEPERIMENT OUTPUT - MODEL WITH TOM-RESTRICTED INFORMATION TRANSPARENCY

The hypothesis has been accepted for the model with full information transparency. However, analysing the influence of social capital on a model where agents do not have full insights in each others preferences, might result in different implications. The hypothesis will be tested by following the same structure as in the previous section. First the group size will be varied and it's effects on the opinion dynamics within the model are analysed. Subsequently, the similar process will be done for the similarity threshold. Both results will be hold against the hypothesis central in this chapter.

THE GROUP SIZE

First of all, the number of students present in the simulation model is varied. As the hypothesis refers to connectivity of the social network, first the relation of the group size towards the size of reference groups is computed. This, as the size of reference groups gives an indication of how many connection each students has, and thus of the connectivity of the social network. The boxplot presented in figure 6.20 shows that the higher the number of students present in the model, the larger the sizes of reference groups. However, not that this relation is less unambiguous as in section 8.2.1, as more outliers spread in a wide range are present in this boxplot. Nonetheless, the group size is considered as a proper input variable to represent the connectivity of the social network.

6

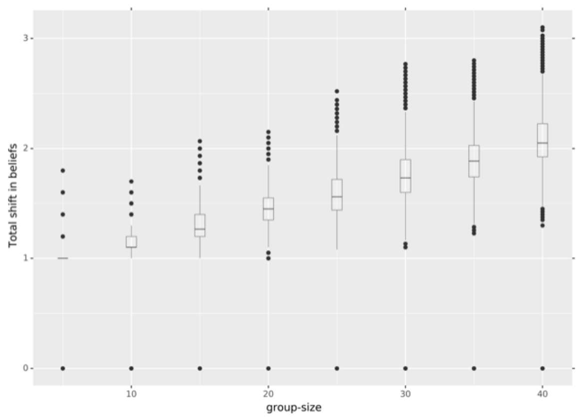

Figure 6.20: The total change in beliefs for different group sizes

When we analyse the affects of this higher connectivity through an increase in students by analysing figure 6.21, two findings emerge. First of all, a higher fluctuation in beliefs within the belief space does occur with a higher group size. However, this increase fluctuation especially occurs in the first step of increasing the number of students, i.e. from 5 to 20 students. The reason for this shift however could be find in the fact that it is fairly important under the five agents, the agent that does own a car, lets other agents carpool with him. When this is not the case, all other agents are not allowed to choose the car as a transport mode possibility, leading to them not being able to evaluate this transport mode as they don't have new experiences with it. This is an example of the path-dependency present in the model. Consequently, when there are more agents present in the model and the 10% of car owners result in a higher number of cars present under students and thus a higher chance of agents being able to carpool and hereby update their opinion on the car as a transport mode. This might also be the reason for an increase in clustering within the full information transparency model, as presented in figure 6.17. However, in the heat map presented for that version of the model, this increase continues when the group size is further increased, which is not the case within the ToM-model.

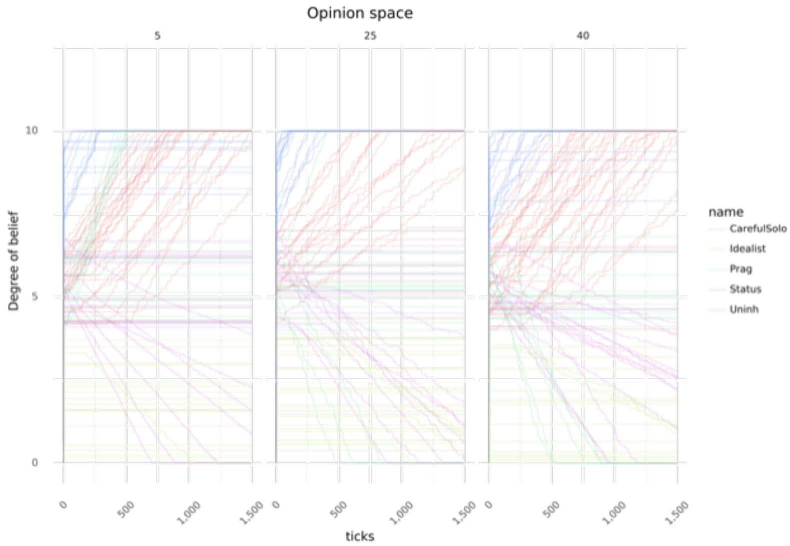

Figure 6.21: Opinion dynamics for different group sizes for the ToM information-restricted model

For the accumulation of beliefs of students on specific points in the belief space, figure 6.22 can be consulted. The colour of the patches in the heat map indicate the percentage of students with a certain belief instead of the number of students (to account for the increasing number of students). The heat map presented in this picture supports the statement that there is a shift in beliefs over time leading to more consensus, just as was concluded in chapter 7, however, this clustering does not appear to a higher degree with an increase of the similarity threshold. Therefore, there cannot be stated that a higher number of students present in the simulation model with ToM-restricted information transparency, representing higher connectivity in the social network, leads to more consensus within this network. Therefore, concerning the relation between group size and opinion dynamics within the ToM-bound simulation model, under all initial parameter settings (other than group size) and the assumptions as presented in appendix A, the hypothesis of an increase in connectivity of the social network leading to more consensus is rejected.

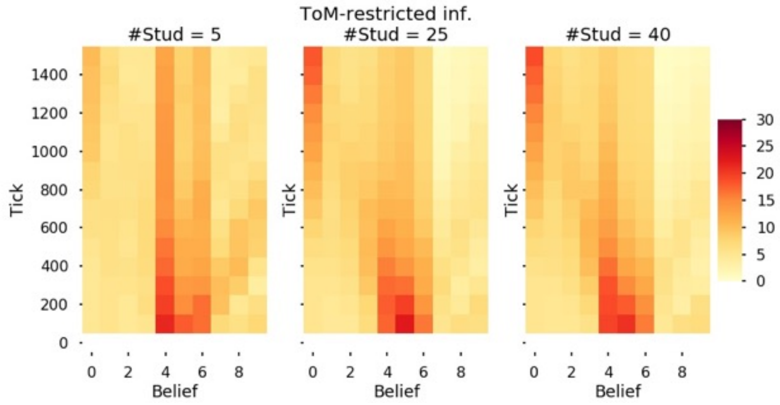

Figure 6.22: Heat map of the number of students with specific beliefs over the simulation with ToM restricting information transparency, for varying group size

SIMILARITY THRESHOLD

Also for the model with bounded information through ToM-capacities of agents, the hypothesis of an increase of connectivity of the social network leading to more consensus will be tested by using the similarity threshold as a representative input variable for varying the connectivity of the network. Figure 6.23 presents the opinion dynamics that occurs under different similarity thresholds (respectively, 5, 13 and 19). This figure does not present very different behaviour within the three scenario's.

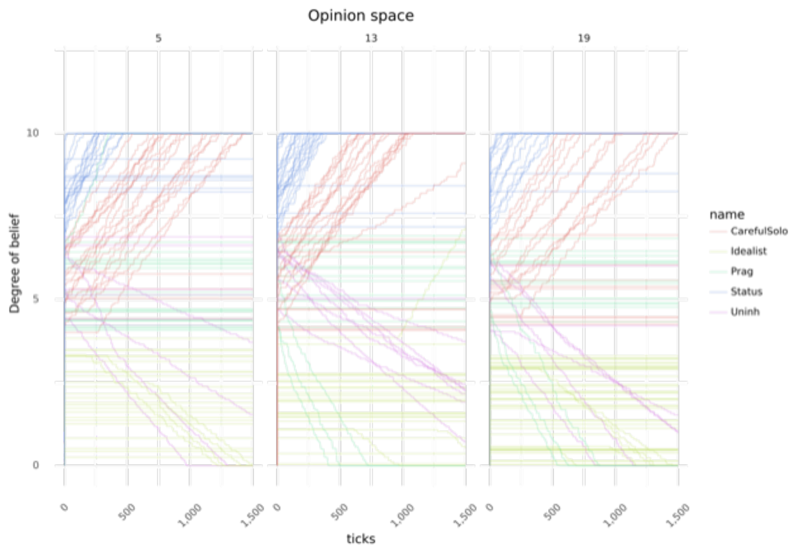

Figure 6.23: Opinion dynamics for different similarity thresholds for the ToM information-restricted model

By analysing figure 6.24, the statement of not significantly different behaviour within the ToM-model under different similarity thresholds can be checked. From this heat map, there can be concluded that it is indeed true that the degree to which clustering of beliefs take place does not increase with a higher similarity threshold. This means, that for the ToM-bounded model, an increase of connectivity in the social network represented by the similarity threshold, under constant parameter-settings (similar to the initial parameter settings of chapter 6.2.1, except for the similarity threshold), and with all assumptions as stated in appendix A active, will **not** lead to more consensus. Therefore hypothesis *H3* is rejected for the ToM-model.

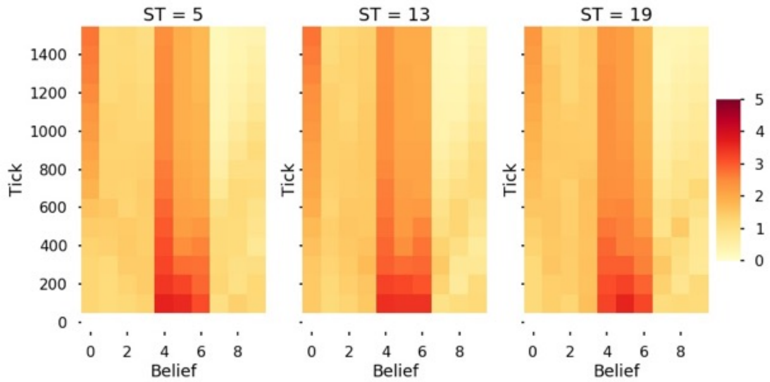

Figure 6.24: Heat map of the number of students with specific beliefs over the simulation with ToM restricting information transparency, for varying similarity threshold

Uniting the conclusions from section 8.3.1 and 8.3.2, as in both sections the hypothesis of more social network connectivity leading to more consensus does not apply to the ToM-model and is therefor rejected for this model.

6

6.4. CHAPTER SUMMARY

The aim of this chapter was to find the typical macro behaviour of action-adapting models, and hold the behaviour within belief-adaption models besides this behaviour to detect similarities and differences. Through related work, an answer to sub question 2 - *What is the typical macro behaviour of models where agents make predictions about their social-context based on the actions of others?* is formulated, by formulating hypotheses capturing their typical macro behaviour. These three findings on macro behaviour in hypotheses form are:

- **H1:** Concerning the opinion dynamics, clustering of opinions appears to a higher degree as the course of the simulation progresses. (Fixed parameters)
- **H2:** Concerning mode share distributions, after reaching an equilibrium in the first stage of the simulation, the shares will remain stable. (Fixed parameters)
- **H3:** Concerning the opinion dynamics, the higher the connectivity within a network, the more consensus can be found. (Experiment with varying parameters)

Through a simulation study on the two belief-adaption models designed within this study, these hypotheses are tested. Following from testing these hypotheses, there can be stated that belief- and action-adaption models as implemented within this study, do not show significant differences in outcomes, as for each model clustering appears to a higher degree as the simulation progresses. Therefore hypotheses 1, 2 and 3 are accepted. However, for the ToM included belief-adaption model, hypothesis 2 does pose a difference between the models. For this ToM-model, different behaviour concerning opinion dynamics occur when the influence of network connectivity is analysed. Where for models with full information transparency stronger consensus arises as (reference) group sizes increase, for theory of mind information restricting models this is not the case, leading to agents staying closer to their personal beliefs.

An overview of the three hypotheses being accepted or rejected for the two models is presented in table 6.3.

	H1	H2	H3
FIT	✓	✓	✓
ToM	✓	✓	✗

Table 6.3: Overview of accepting or rejecting of hypotheses for both model-versions

7

DISCUSSION

"We tend to accept information that confirms our prior beliefs and ignore or discredit information that does not. This confirmation bias settles over our eyes like distorting spectacles for everything we look at."

\- Kyle Hill

This chapter provides a discussion on the model, its results provided by simulation and the respective limitations. Both limitations from the model and from the results are structured by being part of the MAS perspective within this thesis, or the agent-based perspective.

7.1. THE MODEL

The models generated for this study can be seen as models of social comparison, -interaction, autonomous decision-making and opinion dynamics within the case of transport mode choices. To the best of the authors knowledge, the modelling methodology used in this thesis has not been used before to capture a similar system. This implies that possibilities for the comparison of the model structure, assumptions and outcomes have been limited. Therefore, the models are highly subjected to the perspective of the author. Because of this reason, an extra critical examination of the structure and assumptions underlying the models is in place for this section.

LIMITATIONS THROUGH THE LENS OF MULTI-ACTOR SYSTEMS

This subsection provides the limitations posed by the model for capturing human behaviour within a simulation model and hereby contributing to the development of multi-actor systems.

First of all, the largest challenge within the model and also the aspect needed to be discussed the most, is the sociality of agents. As described in Chapter 5, social agents are believed to be agents that can reason about other agents' perception and preferences and that can form their own opinion around this information. This thesis aimed to include all of these aspects, with differing beliefs, social capabilities and social preferences to create autonomous agents with an own 'personality'. However, it remains critical to label the agents within this model as social. For example, (1) agents can only build a positive relation with other agents (i.e., their relation can not decrease in strength), (2) agents will only connect with similar others and thus are not exactly what you would call open-minded, (3) agents always have "equal" relations (i.e., agents always have a connection that is equally strong for both agents) and lastly, (4) within the ToM-model agents cannot increase their insights into others private states through learning about each other. As Liu & Wang (2013) states, one of the adjustments to form a better representation of human relations would be presented when the bounded confidence model would be extended with a random-selection model to allow agents to built relations with some other agents 'different' to themselves. This would just be a start, as many social constructs are still missing within the agent-based models created for this study.

Besides not capturing the fluidity of social processes within the model, the concepts that have been included are often based on non-objective values. However, through sensitivity analysis many of these concepts have been proven to be highly influential when it comes to output variance (e.g., the similarity threshold and the mean ToM deviation). Thus these parameters determine the social character of agents within the model, but little is known about exact parameter settings. As the social nature of agents does form the core of this research, it can be considered a critical limitation that their social abilities have to be questioned.. However, the aim within these thesis was to find differences between ways of letting agents compare themselves to others (with and within ToM restrictions on information transparency and on the basis of beliefs or actions). These differences have been found, and a model with fully social agents has not been required to do so. This does mean that shaping the model from its explanatory form to an exploratory model would be highly challenging.

Furthermore, the validity of the connections made between theories within the theoretical framework is determined through face validity. However, this face validity check is performed by the author, who also designed the theoretical framework and connections between these theories. Because of this, the contributing value of the face validity check can be questioned. Put differently; when face validity is executed by the model designer, theory connections will not be stated to be invalid as when this would have been its opinion, the connections would have been made differently. However, an objective expert on combining these theories within one conceptual model could not be find within the execution of this study. Because the validation of this conceptual framework needs elaboration, face validation has been performed by the author. However, when in future work there are better alternatives, this face validation needs revision.

A third point of discussion with regards to the model, is the restricted world in which agents are placed. Agents have to choose between only three transport modes, i.e.: the bike, car or bus. This excludes many transport options, such as walking, taking a taxi or skateboarding. Furthermore, agents only have memory of their satisfaction for choosing certain transport modes over their last 10 evaluation moments. Highly positive or negative experiences might affect agent preferences for a longer period. Also, agents are limited to their reference group when in comes to social interaction and influences, meaning they are not at all affected by other relations outside of their academical environment (e.g., family and friends from home). Lastly, agents have a certain travel satisfaction level, which is based on different components. However, not included within this satisfaction level are aspects such as traffic, busses being crowded and the weather, as this all is not included in the restricted world in which agents make their decisions. These restrictions imply that agents could have formed other preferences within a more encompassing environment. This, because a different travel experience and a different satisfaction experience, would lead to different personal evaluations. Subsequently, this personal evaluation could come to have a bigger or smaller impact on belief adaption through social influence. This could result in different outcomes when the opinion dynamics is analysed, as clustering could be withhold when personal evaluation would dominantly determine the course of beliefs. Consequently, a different model environment and thus different personal evaluation processes for the agents, would influence the results presented within this study. Therefore, not having included these elements of a broader world poses a limitation for the agent-based model. This has to be kept in mind when considering the results and conclusion of this thesis, as not only the factors that can be measured by science are relevant for model outcomes.

As a last note on the limitations of the model, the opinion strengths are addressed. Within this model, agents can start with a fairly strong opinion on finding certain values important and their relation towards transport modes, but can adjust their beliefs in such way that these relations between modes and values are perceived in a significantly different manner. However, as Lord et al. (1979) states, strong opinions need more convincing in order to shift, as information is retrieved through a filter formed by ones own biases. Therefore, a limitation of the model lies in not capturing 'stuck opinions' and reluctance to revise ones own opinion. In the model, there are agents that are not willing to adjust their beliefs according to other agents' beliefs, but this is only on the grounds of social preferences, not because of other constructs like persuasion and resistance. These are constructs that do play an important role in the willingness to revise ones opinion, and therefore it is considered to be a limitation of the model for not including these elements.

LIMITATIONS THROUGH THE LENS OF AGENT-BASED SYSTEMS

This subsection provides the limitations posed by the model for its capacity towards explaining and understanding human behaviour to a higher degree.

As mentioned in the multi-actor related limitations of the model, the social character of agents within this model can be questioned. This means, that the outcomes of the model cannot be considered representative for the dynamics of beliefs and opinions over time in reality. Because of this lack of proven validity, analysing the model results does not necessarily lead to a better understanding of human behaviour. Many complex processes of social behaviour are not included in this model, which makes it appropriate for the explanatory aim of this research, but not for the examination of real world behaviour.

7.2. RESULTS

Alongside limitations posed by the design of the model, the results provided by simulation runs come with their own limitations. These limitations are similarly structured by their relevance to the field of multi-actor systems and agent-based systems.

LIMITATIONS THROUGH THE LENS OF MULTI-ACTOR SYSTEMS

Having discussed the limitations of the model, the results are topic of discussion in this section. The results of the reference run gave answers towards the hypothesis on clustering increasing as the simulation progresses. However, because of the way these hypotheses are formulated, the conclusions on similarity between belief-adaption models and action-adaption models depend on high-level hypotheses. Because action-adaption models vary in the behaviour they produce, combining findings on these models to more detailed hypotheses has not been not possible. However, because of these high-level hypotheses, the statements on both social comparison approaches being similar or not also only applies to high-level cases.

Secondly, the results of the experiment where group size is varied also requires further elaboration. The experiment section concludes that theory of mind capabilities make agents less susceptible to an increase in social capital. However, this result occurs under the condition that agents added to the group do not bring new 'ingredients'. In other words; no special connection that was not possible with the agents already present in the model can arise with newcomers. In reality, having a larger pool of individuals would increase the chance of meeting someone that one can connect to at a deeper level, which increases the willingness to revise beliefs according to the beliefs of this other person. In this model however, this diversity and individuals being able to have special encounters are not possible. Thus, it needs to be stated that the increase in group size would imply a larger increase in diversity in reality than what is varied with within the models created for this thesis.

Furthermore, the opinion dynamics results show that during the simulation some agents remain zealots, meaning they do not change their opinion over time. Svenkeson & Swami (2015) analysed the effect of zealots present in model runs of opinion dynamics. Svenkeson & Swami's finding was that the presence of zealots counteracts the intermediate states agents need to obtain in order to reach either polarisation or consensus. The end stage subsequently showed less convergence of opinions (Svenkeson & Swami, 2015). However, in the results shown in chapter 6 for every run there is a certain level of zealots present. These zealots however do not result in a blockage towards convergence in beliefs, as clustering is still a result within the models created for this study. Because of this difference in outcomes concerning zealots, a more in-depth analysis of the affect of zealots in a model would be necessary to clarify these differences.

LIMITATIONS THROUGH THE LENS OF AGENT-BASED SYSTEMS

Through the lens of agent-based systems, the following limitation arises.

The results on opinion dynamics as shown in Chapter 6, are a combination of results from many runs. Within each run, the opinions of only one agent is registered. This means that the results as presented in chapter 6 can actually not be seen as a result of social interaction, as the beliefs within these figures have never directly influenced each other. However, when the beliefs of all agents present in one run are registered for multiple runs, the exact same macro behaviour appears. The choice for registering one agent's beliefs in every run has been made because; (1) the processing time of data in Python decreases significantly, (2) this agent takes on the role of each travel type with the same frequency, and thus represents every type and lastly, (3) the exact same macro behaviour is presented. The fact that the exact same macro behaviour arises when separate beliefs from different runs are displayed, does cause some questions to arise. This could mean that the model is deterministic in nature. Therefore, the hypothesis of the model being deterministic has been tested. The exact course of beliefs are found to be unpredictable. However, the direction of belief adaption can be predicted to some degree for each travel type. Strong beliefs on a mode - value relation, will generally be strengthened through personal evaluation. That is, agents that choose a transport mode to satisfy a certain value and already find this transport mode to be positively connected to many values, will often be satisfied with this transport mode and strengthen their beliefs accordingly. Thus, travel types such as status oriented bon vivants that hold a positive attitude towards a transport mode concerning every value (in this case the car), will regularly evaluate this mode positively and strengthen their beliefs. The same holds for disbelief on a transport mode - value relation. In theory, this strengthening of beliefs in either a positive or negative direction could be counteracted by social influence. Thus, agents that shift their beliefs to the positive belief space pole through personal evaluation, could socially influence the beliefs of agents who shift their beliefs to the negative belief space pole, leading to consensus in the middle. However, within this study, such diverging beliefs seldom interact as co-oriented peers already have a more converged set of beliefs. This means that often, strong beliefs interact with strong beliefs, leading to even stronger beliefs. This behaviour is present in all simulation runs, causing the same macro-behaviour to occur throughout every simulation run. Nonetheless, this does not make the model deterministic, as it can never be predicted which agents will contribute to this behaviour and with what speed this behaviour will establish itself. This polarisation of beliefs through having limited possibilities of being influenced by vastly different-minded, is supported by the fact that when all agents are able to influence each other, clustering of opinions does not happen. The opinion dynamics provided by a model where every agents interact with every other agents, is presented in figure 7.1 Thus, when combining this model behaviour with the findings of experiments within chapter 6, concluded is that letting agents interact with a larger reference group (i.e., increasing agents social capital), leads to stronger clustering of opinions until a certain turning point is reached where agents with significant opposing beliefs are able to convince each other of their opinion, preventing polarisation to occur. This situation has not been incorporated in the experiment phase, as having to find each other similar before interacting is an important theoretical foundation of this model. However, it is required to note that this assumption thus contributes to a large extent to the polarisation presented in this study.

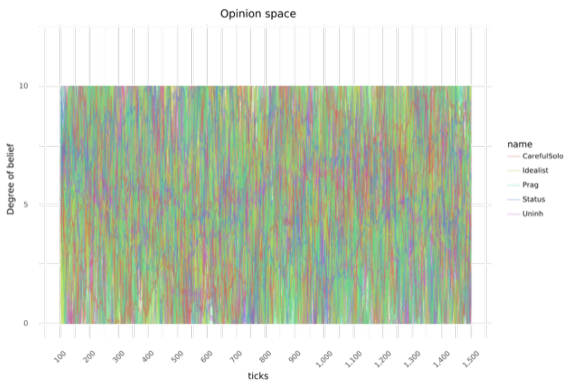

Figure 7.1: Opinion dynamics with all agents socially interacting

Nonetheless, the behaviour of co-oriented belief-interaction causing to strengthen these beliefs to an extreme direction, is not unrealistic. In real life, it is often the case that agents with similar beliefs that already are considered to be fairly extreme, cause each other to develop these beliefs to even more extreme extends. Examples can be found within both left and right-wing extremists (Myers & Bishop, 1970).

8

CONCLUSION

"Research is formalised curiosity.
It is poking and prying with a purpose."

Zora Neale Hurston

This chapter provides an overview of all findings from this study, leading to a final answer to the main research question. In order to correctly present the most important findings of this research, the main limitations and restrictions from the model also need to be highlighted.

Social practice theory places collective cognitive and symbolic structures that are embedded in practices, as a starting point of decision-making. This places underlying individual motives to be secondary criteria for decision-making. In this study, the social practice theory has been used to shape transport mode decisions into a form where social interaction is allowed to influence the decision making process. This has lead to social practices arising from the usage of one of the transport mode options to be divided in three components: their required competences and affordances, and their connected values. The latter plays an important role for the core of this research. Through simulation, agents are able to have personal beliefs on how important they find values and how these values relate to transport modes. These beliefs evolve over time, as they can change through comparing ones own beliefs to other agents within their reference group. This poses a contrast to other models aiming to capture transport mode choices, as social influence often is captured in these models, but this is done by agents comparing their actions and adapting these actions accordingly. This difference has lead to the main research question of this thesis: *How does enabling agents to reason about others' beliefs on social practices affect dynamics of belief and behaviour formation as opposed to action adaption models, with respect to transport mode choices?* . Analysis of related work presented three important findings on models with action adaption:

1. *H1*: Concerning opinion dynamics; clustering of opinions appears to a higher degree as the course of the simulation progresses.

2. *H2*: Concerning opinion dynamics; the higher the connectivity within a network, the more consensus can be found.

3. *H3*: Concerning mode share distributions; after reaching an equilibrium in the first stage of the simulation, the shares will remain stable.

These findings are held against two agent-based models on belief-adaption created for this study. Both models are implementations of a case study of a group of students travelling from their university to a compulsory seminar, with bus, bike and car as transport mode possibilities. The first model contains agents that experience full transparency when it comes to each others beliefs, values and travel satisfaction. In the second model, this information transparency is restricted by agents' theory of mind capacity. The better the theory of mind capacity of an agent, the smaller the deviation of this agent with regard to estimating others' private characteristics. When comparing the outcomes of these two models to the action-adaption model hypotheses, the following conclusions have been presented.

First of all, for both the full information transparency model as the theory of mind restricting information model, clustering does appear and gets stronger as the simulation progresses. Within the theory of mind included model, beliefs are more diffuse and the tendency towards clustering is less strong, but does appear to a higher degree as the simulation progresses. Thus, concerning hypothesis *H1*, all three models have been considered to generate similar behaviour.

In line with the findings for H1, concerning the mode share distributions, all three models also present a similar behaviour. In the beginning, an equilibrium on preferred and implemented modes need to be found by agents, where after the mode shares remain fairly constant. Therefore, hypothesis *H3* is also accepted for both model versions.

Lastly, the effect on opinion dynamics on an increase in connectivity within the social network is analysed (*H2*). Action adaption models are stated to present more clustering through an increase in connectivity of the social network. The same applies to the belief-adaption model with full information transparency. However, with inclusion of theory of mind capacities and hereby information transparency limitations, these increases in social network connectivity seem to loose their power on clustering. Within this version of the model, no increase in clustering is found through an increase in group size nor through an increase in the similarity threshold. Therefore, *H3* is accepted for the full information transparency model, but rejected for the ToM included model.

With these findings, an answer to the main research question can be provided. The answer is as follows: Within the field of transport mode choices, enabling agents to reason about others' beliefs on social practices results in the same opinion dynamics and behaviour as is presented by action adaption models. However, an agent-based model that allows agents to reason about others' beliefs on social practices with limited insight in others' private characteristics through a theory of mind capacity, does provide a different reaction to an increase in the social capital of agents. More specifically, enhancing social network connectivity through increasing the group size or similarity threshold does not lead to more consensus within the theory of mind model. On the other hand, this does lead to greater consensus within the other models of this study. Intuitively, restricting insights into others' private characteristics and hereby providing more nuance to belief adaption, feels like a realistic contribution to the world of agent-based modelling. However, this statement rests on a variety of model and results limitations. This makes it difficult to substantiate the statement of including theory of mind in agent-based models of social influence improving the model and its representation of reality. A selection of these limitations are presented in the following paragraph.

Firstly, from a multi-actor perspective, it becomes difficult to make statements on agents' social behaviour when the sociality of these agents can be questioned. This is the case in the model, as many social constructs are not included or rest on parameter settings that could not have been validated. Also, agents interact within a fairly restricted and simple environment. Excluding external influences as done within this thesis, can result in stronger opinion dynamics than would be the case in reality.

From an agent-based perspective, the nature of behaviour studies challenges to give insight to social interaction and opinion dynamics with respect to the models of this study. There is no golden standard when it comes to the effects of social influence, nor will this golden standard for the explanation of all social phenomena be found in the near future. Because of a lack of proven validity, analysing the model results does not necessarily leads to a better understanding of human behaviour. Many complex processes of social behaviour are not included in this model, making it appropriate for the explanatory aim of this research, but not for the examination of real world behaviour.

Thus, the exact contribution of adding theory of mind capability to agent-based models cannot be provided. However, what can be stated is that the degree to which agents have insight into the private characteristics of other agents does influence model outcomes. Therefore this is an important, indispensable element to elaborate upon when designing an agent-based model.

9

Recommendations, Contribution and Reflection

"From the end spring new beginnings."

Pliny the Elder

This chapter elaborates on the future research that is required to follow-up on questions that arises from this thesis. Also, the scientific and societal relevance of this study are addressed. Furthermore, the link to the Engineering and Policy Analysis MSc. programme for which this thesis has been described. Lastly, a personal reflection on the research progress is provided.

9.1. Future research

Not all knowledge gaps that arise from the discussion sections on the model and the results could be analysed and resolved within this thesis. Four main recommendations concerning future work can be conducted.

First of all, future research should focus on translating social characteristics of humans into ABM. This study contains limited social behaviour and relation dynamics. These limitations could not be resolved from previous research, resulting in a recommendation on further theoretical and applied research on how to give more depth to the social characteristics of agents. Especially the empirical research community within social sciences can help provide these missing puzzle pieces.

The second recommendation for future work, is related to the inclusion of external effects and the broadening of options presented to agents. Because of the rather small scope of the models within in this study, many elements which could have far-reaching effects on opinion dynamics are not included. It is not stated that all these externalities and options should be included for a good model, but their impact on the system must be analysed in order to be able to leave them out without steering the results into a specific direction.

Thirdly, the ease of belief adaption in this thesis should be subjected to further research. Expected is that beliefs connected to values found highly important by agents to not change with the same ease of beliefs connected to values with low importance. A certain level of opinion persistence should come in place. How this exactly would be translated into the model is recommended to analyse in further research.

Furthermore, as noted in the discussion (Chapter 7), the presence of zealots results in a different outcome within the simulation models in this study, than the model created by Svenkeson & Swami (2015). Moreover, Svenkeson & Swami's work shows zealots restricting convergence of opinions to occur, whereas in the model created for this study, despite the presence of zealots, convergence of opinions still occurs. Future research is needed to analyse where this difference in behaviour is a result of. Does this difference arise from a different case study or does the cause lie within the model structure? Determining the cause of this difference and choosing a most representative version might be a step towards standardisation within opinion dynamics modelling.

9

Lastly, the hypotheses used for the comparison between belief adaption and action adaption models within this study are fairly generalistic. For a more concrete statement with regard to their similarities and differences, a more thorough research on related work should be executed. By doing so, more specific macro behaviour for action adaption in the field of transport mode choice models could be obtained, which could lead to more detailed hypotheses and comparison on a more detailed level.

9.2. Scientific relevance

As mentioned in the introduction of this thesis (Chapter 1), more insight in how sociality can be captured in simulation studies can increase the quality of simulations capturing social behaviour and can contribute to the confidence in the legitimacy of computer models within behaviour science. In this study, a theoretical framework for capturing social influence in computer models has been designed and implemented. This theoretical framework could be used as a guideline for capturing social interaction in other case studies and domains.

In addition, through the analysis of the results of the simulation study, the effect and importance of realistic information transparency within social simulation is stressed. At this moment a large share of studies on opinion dynamics and social influence do not capture the limitations to insights in another individuals preferences, goals and motives. Therefore, the finding of the importance of including this aspect brings an important focus point for computer simulations capturing social systems. As an illustration to this statement, the following concrete example can be considered. When generating advice on policy measures regarding the aim to let people choose or not choose specific transport modes, the degree to which people have insight into others' private characteristics does make a difference. The full information transparency model concludes that central interventions can have a relatively larger effect on beliefs -and thus behaviour of individuals within groups- with a highly connected social network than within groups with a relatively low connected social network. However, this conclusion cannot be drawn from the model with ToM restricting information transparency, as more social network connectivity does not lead to more social influence within this model version. This means that both model versions can lead to completely different policy advice. Thus, the finding of theory of mind capabilities being able to steer model outcomes is important to take into account when developing social interaction systems.

Deffuant et al. (2000) proposes the possibility of extending the opinion dyanmics model formed for their study by providing agents with a historical perspective. This historical perspective has been implemented within the models created for this study, by giving agents the awareness of previous travel satisfaction (experienced through the last 10 evaluation moments). By creating awareness about previous satisfaction experienced by choosing certain transport modes, relative satisfaction on current decisions can be determined. When this satisfaction is lower, their beliefs on the specific transport mode being a good choice can decrease, as other transport modes have made them more satisfied in the past. Through this addition, agents look back at the past with every new decision possibility. This is a feature proposed by Deffuant et al. (2000) but not yet included in their opinion dynamics models before, and therefore can be seen as a contribution to the research field.

Another scientific contribution can be found in the conceptualisation of agent values and the value - transport mode relation. As Sen (2009) wrote on values having the reputation of being incommensurable: "a much-used philosophical concept that seems to arouse anxiety and panic among some valuational experts". This study did do an attempt on conceptualising and formalising value-relations, which gave new insights in possibilities for doing so.

Furthermore, this study has been applied to the case of transport mode decisions, but the social practice agents as conceptually and formal designed within this study can be implemented in a wide range of other cases. Requirements for this implementation are a case that (1) allows social interaction, (2) poses agents a finite choice set and that (3) the choice options can be connected to values through agent beliefs. An example of such a case is the decision on whether or not to join a community connected to decentralised energy system, provide ones own energy or stay connected to the main power grid. Another example can be found in the case where individuals make a decision on following a diet with animal sourced food, a vegetarian diet or a vegan diet. The findings found within the case study of this thesis are expected to occur within the above mentioned cases. However, further research should test whether or not the findings from this study repeat themselves within other cases, which would contribute to the robustness of the SoPrA system.

Another scientific contribution arises from the non-Bayesian approach of the models created for this study. Acemoglu & Ozdaglar (2011) stress non-Bayesian models lacking individuals with conjectures about others. Within the agent-based models created for this study, within an non-bayesian environment agents are still given the capacity to make conjectures about others and to process the findings in personal beliefs. Providing non-Bayesian agents with a simplification of these Bayesian capabilities contributes to the research field of non-bayesian models. Through this contribution, it might be possible to find a balance between the encompassing Bayesian approach which is criticised for the high information load agents need to process and the non-Bayesian approach criticised for its ad hoc features and oversimplification of reality.

Lastly, there are various studies that stress proper policy analysis needing to rely on models that do not solely contain rational agents making simple rational choices (for example (McCollum et al., 2017). McCollum et al. (2017) state that social interaction is one of the items frequently missing in research within the transport domain. How to exactly incorporate social interaction in these models is not described by McCollum et al.. This incorporation of social interaction has been performed within this thesis. However, the models are not yet ready to be used for policy analysis, as they are explanatory. The models designed within this thesis can be developed further to become exploratory tools that could help with examining the effects of social interaction on policy interventions. In other words, social influence affecting policy that is created in order to steer individuals into a certain direction (for example, switching to renewable energy) can be tested. This scientific contribution can result in a societal contribution, which is discussed in the next section.

This study does acknowledges the challenges that this field of research still faces and does not turn away from them. This way, step by step the realism of artificial autonomous agents can be increased.

9.3. Societal relevance

Societal challenges subjected to government control are often hard to influence when individuals all make their own decisions, based on their own internal states. This emergent behaviour is hard to predict and thus to control through top-down governance. Agent-based models are a good option for testing policies within complex systems that are difficult to steer centrally (Siebers et al., 2010). While agent-based modelling can be time-costly, testing all these different policy possibilities in reality or implementing a suboptimal policy can bring even higher costs. Therefore, testing different scenario's within an agent-based model is a good alternative. However, this only applies for valid models, as incorrect agent-based models created to serve as policy analysis tools are time-costly and yet result in suboptimal policy advise.

Agent-based models can serve as a means to test the effect of different kind of policy interventions. The Netherlands Institute for Transport Policy Analysis gives four possibilities for behavioural influence: (1) creating discontinuity in order to tackle unconscious decisions, (2) make use of social networks, (3) respond to human nature, (4) make use of the physical environment (Berveling et al., 2011). Within this thesis two of these components are embedded in the agent-based model; responding to human nature and making use of the social network. These two possibilities for influencing behaviour will be discussed separately.

MAKE USE OF SOCIAL NETWORKS

The most important contribution of this thesis to improving agent-based models for cost and time efficient policy advice, is the incorporation of social influence. Policy often strives for the growth of desired behaviour, for which first the processes behind behaviour changes need to be understood. This behaviour is found not to only arise from personal beliefs, but can be influenced by other individuals within a social network that cause beliefs to adjust. To take it one step further; social influence is not only an important process to keep in mind when making policy advice, it can also be subject of the policy measure itself. For example, it turned out that a very efficient way to get citizens to lower their energy usage, was to provide them with the message "most of your neighbours do save energy" (Berveling et al., 2011). Thus, influencing beliefs is possible by utilising the dynamics of the social environment (Berveling et al., 2011). This example is very straight forward, but the exact response to this social influence is not always this clear. The models created within this thesis can be used to better understand the influence of social networks on belief formation and the effects this belief adaption can have on behaviour.

RESPOND TO HUMAN NATURE

When expanding the agent-based models created for this thesis to their exploratory form, the response to small-scale interventions in opinion-dynamics and agent behaviour can be tested. An aspect that helps with executing this within the transport-mode decision case is the 'target group thinking' approach. By dividing the agents within the model into five different groups, there is accounted for the fact that some policy measures affect one group but have no or even a counterproductive effect on another group (Berveling et al., 2011). The models created within this thesis can present the effects of policy measures through direct (individual) influence and indirect (social) influences. This research and future work that can help to make the models within this research exploratory, can help to expose target groups that are receptive to policy measures. Moreover, there can be analysed if resisting groups will be convinced by the shifting beliefs of receptive others, or if this will require more incentives than only social influence. More specified towards the findings within this study, for example the consequences of the amount of individuals able to interact with each other, can give an indication on the chance of social influence resulting in convergence or dispersion of opinions within a community through belief adaption. A small group will not be very receptive to social influence, and will need a more individual approach. Within a larger group not every individual might have to be influenced as the influence of the social network is significantly higher. Similarly, the finding of a higher similarity threshold (i.e., agents finding themselves similar more easily) leading to more clustering of beliefs, could mean that a more homogeneous group is easier to steer centrally whereas a more heterogeneous group would need different incentives to end up at the same desired end-position. However, note that this only applies to situations where individuals have full insight into others' private characteristics, which is often not the case.

9.4. RELEVANCE TO THE EPA MASTERS PROGRAMME

This thesis has been written in order to obtain a MSc. degree within the programme "Engineering and Policy Analysis". The Engineering and Policy Analysis masters programme is focused on supporting decision-making concerning international grand challenges with modelling and analytic techniques. Within this programme, a wide variety of these modelling and analytic techniques is taught, among which agent-based modelling. Through the course of the masters programme, these tools have mainly been used as a means to serve the end of policy analysis. However, as stated by Atkinson et al. (2015), these analytic tools commonly used to support policy decisions for complex problems, often leave room for improvement. Therefore, it was interesting to choose the tools that everyone within the MSc. programme uses as a subject of my thesis instead of addressing the questions these models are designed to answer.

On a higher level, the Engineering and Policy Analysis masters focuses on creating the bridge between society and technology. In this thesis, one of the focus points was improving multi-actor systems, however, through development of the incorporation of social behaviour in these systems. By making multi-actor system a better representation of real human behaviour, the gap between science and practice (e.i., society) can be reduced. In conclusion, this thesis is not a standard example of an EPA MSc. thesis, but it is written with the aim of improving tools used as an input to come to conclusions frequently drawn within the EPA programme.

9.5. PERSONAL REFLECTION ON RESEARCH PROCESS

This research started for me back in august 2018. I spoke to Rijk on Skype, to discuss the possibilities on contributing to his PhD research. The following weeks I was reading into the subject; hopping from one paper to the other, from one subject to another. As I was abroad for a semester, I read in the camper while road tripping, in the mountains, on the beach and in coffee shops of large cities. What I didn't know back then, was that this process of continually finding new related topics and insights would keep occurring, even at the end of the process. (Even more so, I did not know back then that I would get used to spending time on my thesis on odd places and times fairly quickly). However, the process of attaining more information over and over again and not always having time to include this information or to explore this different angle would turn out to be one of the biggest challenges I faced in the process. At a certain point, for me this research simply felt like a labyrinth of papers with interesting findings, in which I just could not seem to find the way out yet. After a while, parts of information seemed to occur in multiple sources and stood out and their connection to the root of this research became clearer. From that moment on, I could work my way through the labyrinth (still not a straight line to walk) and made a coherent research from all the interesting pieces I found and selected to be within my research scope. This for me was the largest challenge but also my largest accomplishment: to say no to certain subjects; to select instead of include.

Another aspect of the process within writing this master thesis was stepping into the shoes of a researcher. I wrote my bachelor thesis within a large company. Of course, this also concerned an academical research, but because of the practical feedback I would get, abstraction would be taken away from topics before it could really establish itself. With writing my master thesis, this was completely different. Not only did I write this thesis within the walls of the university; a company or practical example for sociality *does not exist*. This was completely new for me and I believe it made it possible for me to get a taste of the life of a researcher and I'm really glad it broadened my experiences in this way.

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Appendix A: Assumptions and initial parameter settings

In this appendix the assumptions made in this research and the default parameter settings are described. In chapter 5 the numbers that correspond to the assumption can be trace back to the bigger system component they are part of.

1. **Activity competences and affordances.** A few simplifications have been made concerning the required competences and affordances connected to activities. Regarding the competences, firstly it is assumed that agents need to own a drivers license in order to be able to choose the activity of driving. For affordances, firstly it is assumed that there are always busses driving to the seminar location, with no failures and delays. Secondly, there is always a bus stop close to the University faculty and close to the seminar location. Thirdly, there are always roads and bicycle paths providing a route to the seminar location. Lastly, it is assumed that agents need to be able to access a car (besides be a holder of a drivers license) in order to choose driving as an activity. There are always busses driving to the seminar location (there is no delay) and there are roads and bicycle paths that lead to the seminar location. Lastly, agents will always chose one of the three activity options; taking the bus, car or bike. Walking, taking any other form of public transport, skateboarding or even skipping the seminar and going home directly with hereby not having the social component of travelling together from A to B, are **not** options within this model. In reality, the discrete choice space as presented within this study of course if much broader.

2. **Activity-value relations.** There is a list with values, which agents can attribute a specific personal belief-relation towards the activity to. This list of values gives direction to the nature of the activities to choose from. Only values that are relevant for all actions are included in this study. In this study, the values comfort, relaxation, safety, efficiency, flexibility, fun and environment are taken into account, as these are the values mentioned by the Kennisinstituut Mobiliteitsbeleid to be important for people to make their transport mode choices Olde Kalter et al. (2015).

3. **Agent competences and affordances.** In the beginning of 2015, 1 out of 5 youths in urban areas had a car (Kampert et al., 2018). The chance of owning a car is higher for certain types of students (explained in assumption 19). In urban areas, 53% of youths have a drivers license (Kampert et al., 2018). However, because the amount of agents with cars/licenses present in the model will have a large affect on the opinion dynamics and is not the topic of interest at this point, this parameter will be held constant; 1 in 10 students will have a car and license.

4. **Agent values.** Students have agent-specific weights they attribute to the values. The weight they attribute to values, depends on the type of traveller the student is (see [..] for more information). The higher the weight, the more importance is given to this value by the agent. A higher importance, means that an agent will more often make a decision by reasoning from this value as a starting point. For example; when an agent attributes a weight of 2 to the value "Efficiency" and a weight of 1 to the value "Fun", there will be reasoned twice as much from the starting point of wanting to satisfy efficiency, than from wanting to satisfy the fun-level.

   Furthermore, there is assumed that values stay constant during this study, as their roots are deeply embedded in persons, and will not change during the runtime of this model.

5. **Agents' personal beliefs.** As mentioned in [**4**], students have their own values they find important, but how and if these values are connected to the activities they can choose from, depends on their beliefs. For example, an agent can attach great importance to the value "Environment", but might not belief that the car is not good for the environment. Agent beliefs depend on their student type, and can range from 1 (little belief in a relation between value and activity at all) to 3 (activity and value are very related). These points are translated in the model to random-values, still representing the ranking. So when given a rank 3 to a transport mode link to the value, this means in the model the agent gives a random-float weight of 7 to 10 points to this transport mode. A rank of 2 translates to a random-float weight of 3 to 6 points and a rank of 1 translates into a random-float weight of 0 to 3. This is done to secure agent autonomy, despite they can be of the same travel type.

6. **Agent shared beliefs.** Shared beliefs are determined by inspecting each value-activity relation, and if the beliefs attributed to this relation by agents is do not differ more than a certain threshold from each other, they are considered to be shared. In other words, shared beliefs are not predefined, but can develop over time and are registered by an agent.

7. **The co-oriented peer reference group.** When agents have 4 or values that they roughly attribute the same weight to, they consider each other as co-oriented peers. When an agent considers themselves co-oriented with another agents, this does not mean that this is a two way relationship. Agents make this decision for themselves. Furthermore, there is assumed that the first time an agent comes to the conclusion another agent is just like him in his perception, the influence strength between the agents is not directly increased. There is assumed during their first interaction, agents will be a bit more observant and will attribute a conclusive influence strength to their relationship with another agent the from the second interaction on.

8. **Agent Prosociality.** Prosociality is given to the students with an initial parameter setting determined by a normal distribution with a mean of 0.48 and a standard deviation of 0.42. This means that initially, the prosociality of an agent is not dependent on the travel type of the student, but purely random. When a student has

a low prosocial-score, a "proself" attitude is on the other end of the scale. These attitudes influence how they interact with other students. When a student is more prosocial, they will have a larger willingness to cooperate and thus will shift their beliefs more quicker to the beliefs of their like-minded. Also, prosocials care more about equality in outcome. However, this is not the case when the other agent is not prosocial, than this will cause fear of exploitation and keeps the prosocial agent from adjusting their beliefs (Declerck & Bogaert, 2008).

9. **Agent ToM.** Theory of mind has five levels, which arise from the level of prosocialness of students. Table A.1 shows the relation between prosocialness and ToM capability that is assumed. This level of ToM-capability, subsequently determines the error with which one predicts the values, beliefs and travel satisfaction of other agents. In the model, this is translated as the real value + or - a number drawn from a normal distribution with a mean of 0.5 + a value determined by ToM-capabilities of the predicting agent and the standard deviation determined by the ToM-capabilities of the predicting agent. Thus, the better ToM an agent has, the lower the mean of the normal distribution that represents the deviation and the lower the corresponding standard deviation. This choice has been made, because a higher theory of mind-capability does not only mean that an agent more adequately predicts social-related values of other agents (i.e., has a lower mean in the normal distribution that represents the deviation), but also knows what to look for and will diverge within a smaller bound, because of the more accurate predictive skills. Lastly, whether an agent substract or adds the deviation to the real value in the model is determined by the fact if the agent is an overestimator or an underestimator.

	Prosocialness (x)				
	$0 < x \leq 0.2$	$0.2 < x \leq 0.4$	$0.4 < x \leq 0.6$	$0.6 < x \leq 0.8$	$0.8 < x \leq 1.0$
ToM-level	1	2	3	4	5
Extra-mean deviation	0.8	0.6	0.4	0.2	0
Standard deviation	1.5	1.2	0.9	0.6	0.3

Table A.1: Theory of mind related deviations as a result of prosocialness-levels

10. **Agent cooperation.** When both agents are prosocial, their willingness to cooperate is optimal (influence strength + 1), when one of the agents is medium prosocial the willingness to cooperate is lower (influence strength + 0.4) and when one or both agents are not prosocial, there is no willingness to cooperate. The influence strength is added to the existing influence strength of the relation between agents. **[11]** Explains how this affects the interaction between agents.

11. **Social relations.** Relations between agents are based on their influence strength which is developed over time. The influence strength stems from an agent's prosocialness, the like-mindedness with the other agent and the number of times they have interacted. A larger influence strength, means that agents will adjust their beliefs more easily with each other. For example, when the influence-strength between agents is higher than 25, their beliefs will move with 0.01 points to each

other, but when this influence-strength > 50, the belief of an agent will move towards the belief of the other agent with 0.05 points. Eventually, the strength of their relation influences the degree to which they socially influence each other. However, there are limitations to the influence of this relation between agents on their behaviour. For example, as is partly mentioned in the following assumption point of carpooling, agents do not choose their 'carpool-buddies' based on their relation, but this process is performed by a first come first serve principle. However, this process might give a better representation of reality when the agents allowed carpooling with the driver, are agents with (1) the preference of driving to the seminar, and (2) the closest connection to the driver or, if the driver has limited connections but is willing to take passengers (3), agents with the most connections with other passengers. This process of carpool-selection based on social ties is not included in this version of the simulation model, which can be seen as a limitation.

12. **Carpooling.** When an agent does not have a car on their own, carpooling is possible when another agent which does have the affordance of a car, and is willing to share their care chooses to take the car to the seminar. However, a first come first serve principle is used with determining who will be able to get in the car with the driver. Max 5 agents are allowed in each car.

13. **Travel satisfaction.** Travel satisfaction is a product of travel stress, -enjoyment, intrapersonal- and interpersonal (social) comparison (Abou-Zeid & Ben-Akiva, 2011). Originally, this formula also contained satisfaction about the activity at the destination, but since this is not within the scope of this research, this part of the formula is not taken into account. Stress is determined by how important one finds the values of safety, efficiency, flexibility and environment, and how much the by the agent chosen activity satisfies these values, on account of the belief-relation of the agent between these values and activities. When one does not attribute much weight to these values, this part of the formula will be taken less into account in the entire calculation.

    Then, enjoyment is determined by the values comfort, fun and relaxation. Just as with stress, the level of enjoyment is a result from the extent to which the chosen activity satisfies these values according to the belief-relationship between values and activity of the agent.

    The intrapersonal comparison is the satisfaction of this choice, compared to an agents satisfaction during their previous ten decisions. There has been chosen to take the last ten transport mode choices into account, because it is long enough to compare the current situation with an average of past situations, but to not take situations in account that are very different from how the agent is now situated in the social network.

    The social comparison part accounts for how an agent thinks they are doing compared to other agents who are part of their like-minded group. Some agents will not have a group of like-mindeds, and consequently are not able to reason about their satisfaction compared to others. Proself agents find it important that they are equally as good or better than other agents. Prosocial agents however, care about the whole group and that everyone is doing well. They do not want to be far removed from the rest of the group when it comes to their travel satisfaction.

These are the only components taken into account when determining the transport satisfaction, but of course normally this satisfaction is determined by a larger spectrum of criteria. For example, how someone is doing that specific day, if there were any delays during the trip, how busy traffic was etc. Because of time constraints, these aspects are to be added to this study in a follow up research.

14. **Activity implementation history.** As a result of their values and beliefs, agents will make a choice for their transport mode; the implementation. There has been chosen to only make uni-modal transport possible; multi-modal transport is left out of scope. Everyone is aware of all transport options. The history of the last 10 decisions and the experiences satisfaction from these decisions is registered by agents.

15. **Building a relation** When agents find themselves similarly enough with regard to their values, there is an option for them to start building a relationship. The strength of this relationship is indicated by the "influence-strength" variable of the link between agents in the simulation model. The rate with which this strength increases, depends on the prosociality of the agents (as described in [**10**]). The exact values for prosocialness leading to certain influence-strength are presented in table A.2, where a prosocialness between 0 and 0.4 is represented by the number 0, a prosocialnesslevel between 0.4 and 0.7 is represented by the number 1 and a prosocialness higher than 0.7 is represented by the number 2.

		Prosocial of self		
		0	**1**	**2**
Prosocial of other	**0**	0	0	0
	1	0	0.25	0.5
	2	0	0.5	1

Table A.2: Influence-strength increment subjected to prosocialness

However, it is important to note that with building a relation, in this study there is only a possibility for working on this relationship in a positive manner, meaning an increase in the connection between agents. Another option would be agents having a decreasing connection over time, as they dislike each other. This is a possibility in reality, but one of the limitations of the model for not including this.

16. **Extend to which agents influence each others beliefs** The extend to which agents are willing to adapt their own beliefs towards the beliefs of someone else, depends on their relation (i.e., influence-strength [**15**]. The better their relation, the higher their reciprocal influence-strength, and thus the higher the shift in belief-points towards the beliefs of the other agent. The exact shift in beliefs according to the influence-strength between agents is presented in table A.3.

	Influence-strength (x)		
	$0 < x \leq 25$	$25 < x \leq 50$	$x \geq 50$
Points of belief adaption	0.05	0.01	0.025

Table A.3: Belief-adaption subjected to influence-strength of agent-relations

17. **Group size** An initial group size of twenty has been chosen. This has been chosen by trial and error, as when combined with a similarity threshold of 7 [**17**], there are students influences by other students, but there are still students that stick with their own beliefs. Also, a group size of 20 allows all student types to be implemented exactly 4 times, which erases the amount of students from each type from being an influential parameter.

18. **Share of students owning a bicycle**. An initial bicycle percentage of 75% has been chosen, since it concerns a University Faculty in The Hague, where many international students study who not all own a bicycle. The exact share of students with a bicycle is not known, and thus this variable will be object for sensitivity analysis to find out what it's influence on the model KPI's is, and thus to find out the importance of a just parameter-setting. An additional assumption towards bicycle owners, is that they are not able to carry other passengers on their bike in the model.

19. **Share of students owning a car**. The number of car owners is an important affordance-element of agents, as their options are more limited when less cars are owned by the group (for private transport and carpooling). The initial setting of this parameter is 10%. This initial parameter setting is based on the average percentage of students in urban areas who own a car (Kampert, n.d.). This share of car-owning students is subject to more external factors than included in this model, and thus this parameter will be subject of a sensitivity analysis in order to find out whether or not the right representation of this share is a must for an accurate model. Some agents are of a travel type that attains more value to owning a car (such as the status oriented bon vivants) and respectively have a higher chance on owning a car (as opposed to for example the independent idealist).

A

20. **Similarity threshold.** The initial maximum amount of points that agents can differ in with regard to their value-importance and still see each other as co-oriented peers, is set to 7. This means, that for each of the seven values, an average of 1 point (out of 10) difference is allowed for co-oriented peers. This initial setting foll owes from the intuitive thought that agents do not completely have to be alike in order to see themselves as co-oriented. A difference of 2 points within a value, still means that often more or less the same priorities are given to the same values.

21. **Opinion strength.** Opinion strength (i.e., the degree to which someone can be convinced of other view points) does not change over time. Research suggests that prior views can differ in strength and that this strength can increase or decrease due to arguments of others (Yu et al., 2016). The strength of ones viewpoint then

partly determines whether or not one is open to shift their beliefs. In this research, this opinion strength is left out of scope and remains constant. It's importance is not neglected, but this is part of the future works due to time boundaries.

22. **Location of affordance**. When one is in possession of a specific affordance, agents will always have access to their affordance(s). Because agents can choose from all their affordances, this implies that they brought all their options to lecture and are not reluctant of letting some options behind (such as their car). However, in reality this must be more path dependent, as one chooses their mode of transport to go to their university faculty, which will most probably also be the mode of transport used to go from the faculty to the seminar, since that would make it more convenient to directly bring the vehicle home after the seminar.

23. **Personal and private characteristics.** Although agents only compare themselves to others based on private characteristics, and adjust their private characteristics accordingly, public characteristics do play a small role in this belief-updating process. The influence of public influence can be found in the fact that agents only update the beliefs on the mode which their co-oriented peer has chosen during that decision moment. This assumption has been made for two reasons. First of all, because updating personal characteristics does not necessarily mean that public characteristics are not observed at all. Updating beliefs through social influences is performed by interpreting the reason for other agents choices. For example, thinking another agent chooses the car because it is efficient and comfortable. This does not require updating the beliefs on all other transport modes as well, predicting why someone chooses for an option requires less information than predicting why someone did not chooses for all other options. This immediately poses the second reason for this assumption; the quantity of information that needs to be processed for belief-adaption. It is found that the short-term mental storage capacity is set to a maximum (Cowan, 2001). There can be debated whether this number is 4 or 7 on average, but the point here is that this maximum does not enable all elements to be evaluated when all beliefs on all transport mode - value relations is being updated. Because of these two reasons, there has been chosen to let agents only update the beliefs on value - transport mode relations for the transport mode(s) co-oriented peers choose.

APPENDIX B: MODEL PROCESSES

In this appendix, all processes that are completed during the set-up phase of the model and all actions executed by agents in the model during the go-phase are described. The model narrative describes all processes in order of performance. First, the actions of the setup phase are presented, followed by the actions executed during run time. All described actions in the run phase are executed by students.

SETUP PHASE

- Creating students
  - Creating *numstudents* variable amount of student-agents
  - Making them a specific travel type (status driven – careful solo – pragmatic mover – idealist – uninhibited) **[..]**.
  - Giving each student a specific theory of mind level and corresponding prosociality.
- Creating activities
  - Connecting activity of “Biking to lecture” “Driving to lecture” and “Taking bus to lecture”.
  - Connecting activities to all values.
- Providing students with their personal values and beliefs
  - With the travel type of an agent as indicator, an agent is provided with personal values and with beliefs about value-activity relations.
- Setup affordances and competences
  - Create all affordances from table 3.1.
- Setup activity elements
  - Create links between activities and their required affordances and competences
- Setup student elements
  - Giving students weights to specific values, to create a value-profile in which they can prioritise certain values over others (all according to the travel type of the student).

- Giving students belief-relations between values and activities (according to the travel type of the student).
- Providing students with their personal affordances and competences.

- Setup the possibilities and limitations of students given by their physical environment
    - Match all activity requirements with the belongings of a students. When belongings do not match with requirements of an activity, this activity becomes off limits for this student. There is only one exception: when a student does not have a car, carpooling might still be an option.

RUN PHASE

- Register which students might be willing to share their car if they choose to use it
- Sort values
    - Based on the weight attributed to values, they are chosen to be the target-value of this decision round.
- Match activity to target-value
    - First register which activities are and are not available based on activity-element and student-belongings.
    - Register if carpooling is possible when driving is not an activity an agent can perform on their own; i.e., someone is willing to drive you and the car is not full yet. (Because of this, students with car first choose if they will use it and if they allow others to travel with them).
    - Choose an available activity that serves the target-value best according to the agent's beliefs.
- Personal evaluation
    - Determine the stress and joy experienced by choosing the implemented activity.
    - Determine if this stress and joy was higher or lower than during the previous decision moment.
- Social evaluation
    - Agents determine which agents they think are like themselves, based on their values.
    - Based on their co-orientedness and prosociality, agents update their relation and thus their influence strength.
    - Determine if the travel experience of oneself was better or worse than that of the agents they feel connected to (i.e., co-oriented peers).

- Determine travel satisfaction
    - Through the personal an social evaluation, the travel satisfaction can be calculated.
- Update personal beliefs
    - As a result from social influence and experiences travel satisfaction during their previous decision, agents update their beliefs.

APPENDIX C: STUDENT TRAVEL PROFILES

This appendix describes the different student profiles that are used to give shape and internal consistency to the agents in the simulation study. *The* student does not exist when describing travel behaviour, and so it does not exist in the model. Five different types of students when it comes to their travel behaviour have been defined, based on the report of Coffeng (2015). These five types are described in this appendix. For each student profile, their values and beliefs are summarised in a table. In this table, a point scale indicates the importance given to a specific value and the conviction about an activity-value combination. Here, the points vary from 1 to 3, where 1 means an agents attributes low importance to a value or sees no to a very thin relation between the value and an activity and where 3 indicates high importance and beliefs. Eventually, these relative scores are translated into agent-specific values in the model.

STATUS-ORIENTED BON VIVANTS

> *"I want to have a Porsche when I grow up: I love speed and pretty cars. I hardly ever ride my bike, since I rather ride my scooter. It's a whole lot faster and I think it's more relaxed"* - Milan (Coffeng, 2015)

Status oriented travellers are concerned how others perceive their travel behaviour, and thus often choose transport modes that are linked to prestige in their opinion (mostly the car). Because of this, this travel type relatively often owns a car and a drivers license. Besides status, this group also attaches great value to freedom. Possibilities for delays and a lack of personal space can form a barrier for status oriented students to choose public transport as a transport mode. Besides finding it important what others think, this group also prefers travelling with other people because for them this means higher pleasure experienced from the trip. Table C.4 shows the points attributed to values for the status oriented travel type, and in table C.5 the beliefs about the relation between these values and the different activities to be chosen from is shown.

Values						
Comfort	Relaxation	Efficiency	Safety	Flexibility	Fun	Environment
3	2	3	2	3	3	1

Table C.4: Status oriented traveller - values

		Values						
		Comfort	Relaxation	Efficiency	Safety	Flexibility	Fun	Environment
Activities	Bike	2	2	3	2	2	2	3
	Car	3	3	3	2	3	3	1
	Bus	1	1	1	2	1	1	2

Table C.5: Status oriented traveller - beliefs

UNINHIBITED ROAD USERS

> *"I'm fine with travelling by public transport, as long as I don't have to change from bus three times."* - Boris (Coffeng, 2015)

This is the smallest group under students; the uninhabited travellers. They are not notably positive or negative towards transport modes, but see travelling as necessary and choose the transport mode which is most practical at that moment. Also towards the possibility of travelling together or alone the uninhibited travel type is very neutral, just as long as they reach their destination. Table C.6 shows the points attributed to values for the uninhibited travel type, and in table C.7 the beliefs about the relation between these values and the different activities to be chosen from is shown.

Values						
Comfort	Relaxation	Efficiency	Safety	Flexibility	Fun	Environment
1	1	3	1	1	1	1

Table C.6: Unhibited road user - values

		Values						
		Comfort	Relaxation	Efficiency	Safety	Flexibility	Fun	Environment
Activities	Bike	2	2	2	2	2	2	3
	Car	2	2	2	2	2	2	1
	Bus	2	2	2	2	1	2	2

Table C.7: Status oriented traveller - beliefs

C

CAREFUL SOLO TRAVELLERS

> *"I get annoyed by aggressive drivers and people who are not focused in traffic. Or by crowded, stuffy buses; I once saw someone faint."* - Annika (Coffeng, 2015)

The careful solo traveller attaches a great amount of value to freedom and personal space. This often results in a positive attitude towards the car. Because of this, together with the status oriented travel type, the careful solo road user is the type which most often owns a car and a drivers license. This independent travel type wants to experience control over the situation and thus does not want to be dependent on others. A private vehicle, controlled by themselves is their favoured travel scenario in order to secure their need for feeling safe and free. Table C.8 shows the points attributed to specific values by carefully solo travellers, and in table C.9 the belief relationship between these values and the activities is displayed.

Values						
Comfort	Relaxation	Efficiency	Safety	Flexibility	Fun	Environment
2	2	3	3	3	2	2

Table C.8: Careful solo traveler - values

		Values						
		Comfort	Relaxation	Efficiency	Safety	Flexibility	Fun	Environment
Activities	Bike	2	2	3	1	2	2	3
	Car	3	3	3	3	2	2	1
	Bus	1	1	1	2	1	1	2

Table C.9: Careful solo traveler - beliefs

PRAGMATIC MOVERS

> *"If I would use public transport daily, I would feel lazy. I just like being on my bike and don't enjoy the mass in busses"* - Joep (Coffeng, 2015)

Pragmatic movers love to be in the outdoors and exercise and extend this preference to their travel behaviour. Their best case scenario is where they can combine their preference for an active lifestyle with social occasions. The pragmatic type doesn't worry about the reputation a transport mode might carry, as long as the vehicle brings them from A to B. Public transport can give the pragmatic mover stress, as being dependend on the bus schedule and crowded busses are things that generate aversion with this travel type. The importance given to values by pragmatic movers is shown in table C.10. Subsequently, the belief-rate of pragmatic movers on specific value - activity relaitons is described in table C.11.

Values						
Comfort	Relaxation	Efficiency	Safety	Flexibility	Fun	Environment
2	1	2	1	2	3	2

Table C.10: Pragmatic mover - values

	Values							
		Comfort	Relaxation	Efficiency	Safety	Flexibility	Fun	Environment
Activities	Bike	3	3	3	2	3	3	3
	Car	2	2	2	2	2	2	1
	Bus	1	1	2	2	2	1	2

Table C.11: Pragmatic mover - beliefs

INDEPENDENT IDEALIST

> *"I rather not drive a big range rover, it uses to much gas. I care about the environment and the earth, and do not want to harm this any further"* - Anne (Coffeng, 2015)

As can be derived from the name, independent idealist strive for a better world and are willing to contribute to this task. They are venturous and have a clear opinion. Related to the transport topic, this means that they are hesitant towards traveling by car. Compared to the other travel types, they have a relatively positive attitudes towards the bus, but are often also more positive about traveling by bike. They find safety very important, and raise this topic above other practical values such as efficiency. The independency of this travel type subsequently lets them attain high value to flexibility in transport, so they can go their own way whenever they want. The importance attached to the seven values of the independent idealist are presented in table C.12. Lastly, the beliefs about specific value-activity relations are presented in table C.13.

Values						
Comfort	Relaxation	Efficiency	Safety	Flexibility	Fun	Environment
2	2	2	3	3	2	3

Table C.12: Independent idealist - values

	Values							
		Comfort	Relaxation	Efficiency	Safety	Flexibility	Fun	Environment
Activities	Bike	2	3	2	2	3	3	3
	Car	3	2	2	3	2	1	1
	Bus	2	1	2	3	2	2	2

Table C.13: Independent idealist - beliefs

C

Appendix D: Sensitivity analysis

In this appendix a detailed description of the performed sensitivity analysis and its results is presented. In the first section, the executed sensitivity analysis for the model with complete information transparency between agents is presented. In the second section the sensitivity analysis for the model where information transparency is restricted by theory of mind capabilities is presented.

As is described in the main text, for this study a global sensitivity analysis driven by Sobol indices is performed in order to see which inputs have the largest effect on output variance. A full overview of all inputs which have been included in this sensitivity analysis and the range in which these inputs will be varied is presented in table D.14.

Input Variable	**Variance range**
Random-seed	[1, 100000]
Number of students	[5, 50]
Similarity threshold	[5, 25]
Percentage bike-owners	[20, 90]
Percentage car-owners	[10, 90]
Increase in influence strength	[1, 5]
Adaption in satisfaction per evaluation	[0.5, 5]
Update of beliefs per evaluation	[0.05, 5]

Table D.14: Input variables subject of sensitivity analysis

There can be made a distinction between two types of input variables: (1) input variables which outline the scenario of the simulation run and (2) input variables which are the real unknowns. The first category are the variables which can be determined by an exact description of the modelled environment. These are the number of students, the percentage of students that have a bike and the percentage of students that have car. With a very specific case study, statistics about these variables can be found and inserted into the model. The second category however, is more difficult to fill in. These are the input variables where, as is known for now, are no concrete numbers known for. Under this category we consider the input variables similarity threshold, speed with which agents increase their relation strength, degree to which agents update their satisfaction-level through one evaluation moment and the points that agents shift their beliefs with towards beliefs of others through one single update moment. For this reason, when this category of input variables contributes to a large share of variance within output variables, this poses more uncertainty around the model than when this is the case for the first category. In other words, uncertainty posed by category 1 input-variables stresses the need for well-founded and substantiated knowledge of the case that is implemented in the model, whereas uncertainty posed by category 2 stresses the need for further research in order to narrow down the boundaries of possibilities for these values.

First of all, the random-seed is an input variable that is subjected to the sensitivity analysis. The random number generation process within the NetLogo model can cause the model to take a certain turn, as there are multiple variables influenced by random number. Therefore, it is helpful to analyse the affect of this variance in random-seeds to see the importance of this process on the model uncertainty.

Than, the number of students. The number of students can be changed in the model, which might affect interaction between agents. Therefore this input variable is part of the global sensitivity analysis, and is varied with from 5 students up to 50 students. In subsection 6, there has been concluded that there can also be more than 50 students present in the model for it to still work properly. However, these boundaries have been set in de sensitivity analysis since this is a proper maximum of students all having to travel together from one lecture to another and the time requirement of wide ranges has to be taken into account. Therefore, this is considered as a proper boundary.

Subsequently, the similarity threshold is another input variable used to examine the sensitivity of the model. The similarity threshold stands for the maximum amount of belief-point differences agents can have to still consider themselves to be like-minded. The boundaries of this threshold are set to [5, 25]. Per agents, there is a maximum of 210 belief-points to be distributed over value-transport mode relations. A maximum of 20 belief points than might not seem as much, but when running the simulation for different thresholds, a maximum of 25 points already results in a situation where all agents are influenced by at least one other agent. Because of this reason, the threshold is put on 25 and not higher. The same counts for the lower boundary; a threshold of five results in a situation where non of the agents is influenced by another agent, causing an expansion of the boundaries on the lower part to not increase the value of the analysis.
Furthermore, the percentage of bike-holders will be varied in order to examine the robustness of the model. The boundaries of this variation are set to [10, 100].

A very similar variable, which also describes one of the affordances of agents, is the percentage of car-owners. The boundaries of this variation are set to [10, 100].

Lastly, three variables that are less straightforward form an important part of the sensitivity analysis. These variables have been indicated as category 2 input variables:

- Satisfaction level: the increase and decrease rate of satisfaction of agents per evaluation round. The boundaries of this variables have been set to [0.5, 5.].

- The increase rate of the relation-strength between agents. This increase and decrease depends on the prosocialness of agents, but there is one starting point that can be varied within the sensitivity analysis. This is the relation-strength increase rate between two prosocial agents. A prosocial agent interaction with a medium prosocial agent increase their relation by half of the rate and two medium prosocial agents by half of the latter rate. The boundaries for this variable have been set to [1., 5.]. A higher value, means that within a shorter amount of time strong relationships have been formed between agents.

- Belief shift: this is the degree to which an agent shifts its belief towards the belief of another agent. Because of its subjectiveness and at the same time importance for the model, including this variable within the sensitivity analysis is a must. The boundaries of this variable have been set to [0.05, 2.]. A higher value than 2 would mean that through one evaluation round, agents can update their beliefs from being convinced of a specific relation to not hold this opinion at all. Because this would result in vast fluctuations, the boundary has been set to 2.

The three variables presented above are not fully backed-up by previous research, and therefore the value that they have in the reference run, is part of a large uncertainty of the model and must be in more depth examined in further research. However, since the variables are indispensable for the simulations study, there had to be made an intuitively plausible estimation for these values. This makes it extra important to analyse these variables on their contribution to output-variable variance.

With these eight variables, 100 simulations will be run. This results in a total of 1800 experiments. The output variables of interest within this sensitivity analysis are the following:

1. Sizes of reference group: The average size of groups of students who find themselves alike and influence each others beliefs.

2. Average change in beliefs: The average change in beliefs as a result of a single evaluation.

3. Average share of socially influenced students: The average amount of students who have at least one other student that they consider as co-oriented and that they interact with.

D.6. SENSITIVITY ANALYSIS OF THE MODEL WITH FULL INFORMATION TRANSPARENCY

First of all, the model where agents have full insights into the beliefs, values and travel satisfaction of other agents in order to make up their own mind is subjected to the sensitivity analysis.

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PEARSON CORRELATION COEFFICIENTS

As a first step of this analysis, the Pearson correlation coefficient (r) is computed in order to visualise the relationship between each individual input variable and each output variable of interest. The linear trends are presented within the bivariate scatter plots of figure D.1 to D.3. This is an important step within this sensitivity analysis. This is because later in this sensitivity analysis, there will be given an overview to the share with which an input variable contributed to the variance in the respective output variable. However, if from the Pearsson correlation test the conclusion can be made that non of the input variables are strongly correlated to variance in the output variable, than the contribution that is presented in these figures concern a small shift in the actual model outcomes. For example; a contribution of 100% to a variance of the output variable sounds as a lot, but not when this is 100% of 0.000001% shift of the output variable. Therefore, a first selection of influential input variables and vulnerable output variables is made in this subsection.

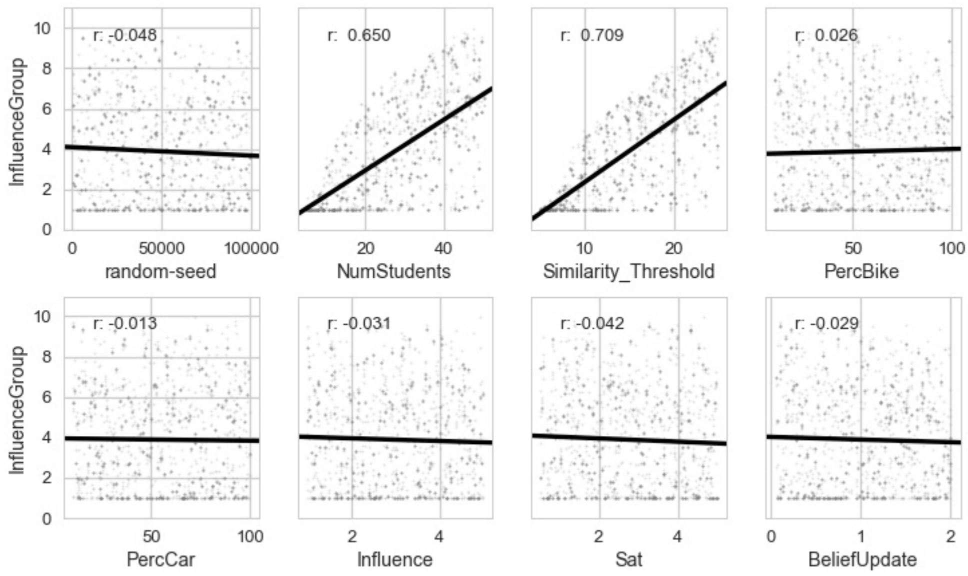

Figure D.1: Pearson correlation between input variables and the average size of reference groups

In figure D.1, one can see that the average size of reference groups in strongly correlated with the number of students within the model. This ofcourse cannot come as a suprise: a larger number of students, means that there are more students that one can feel related to. The structure of the model than results in larger reference groups, also because their is not a maximum number of students within one reference group. This is an assumption, as it might be the case that in the real world larger groups might split in smaller reference groups. This assumption is further discussed in chapter ... The other correlations between input variables and the size of reference groups is less significant.

In figure D.2, there is shown how the input variables affect variations in the output variable of the average shift in belief-points with every evaluation moment. As can be seen from the bivariate scatterplots, there are stronger correlations between more input variables and this output variable than in D.1. However, it might be the case that one or two variables cause the stronger correlation with other variables and the output variable through higher order interactions. The next paragraph will further elaborate on this.

Lastly, D.3 displays the correlation between all input variables and the average share of socially influenced students. The strongest influence on variance of this output variable is caused by the number of students. This makes sense since more agents in the simulation will cause a higher amount of candidates for social comparison, interaction and influence. Besides the similarity threshold, the other variables seem insignificantly correlated to fluctuations in this outcome variable. The exact individual influences and interactions between the input variables for higher order interactions will be elaborated upon in paragraph D.2.

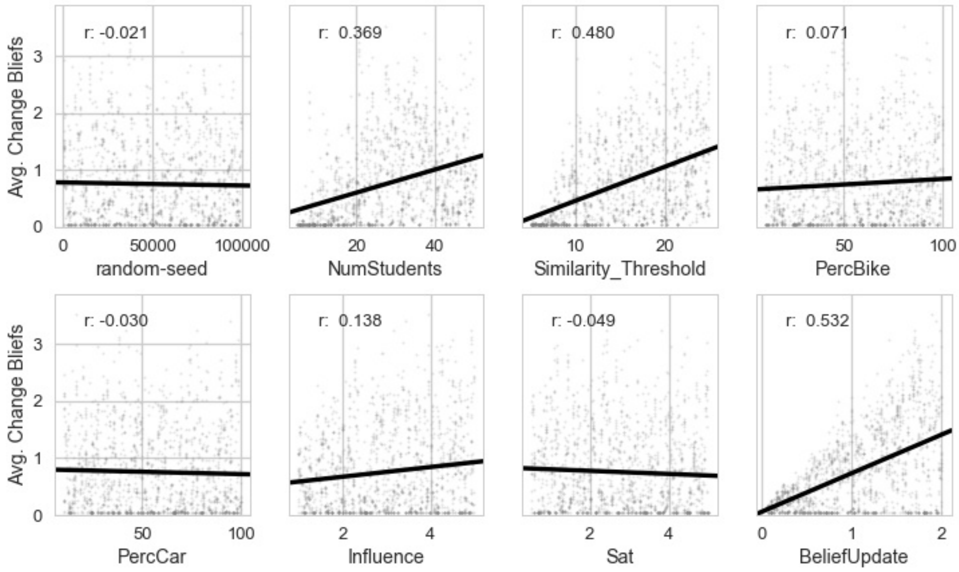

Figure D.2: Pearson correlation between input variables and the average change in beliefs during each evaluation process

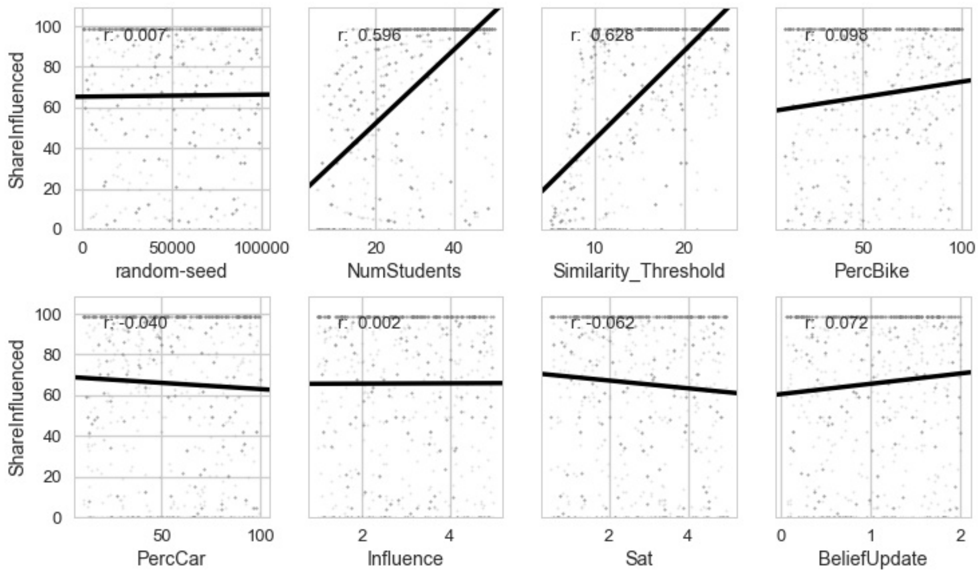

Figure D.3: Pearson correlation between input variables and the average number of socially influenced students

In conclusion, every output variable seems to be sensitive to fluctuations in the numbe rof students present in the model and to the similarity threshold. Furthermore, the output variable "Average change in beliefs" seems to be sensitive for fluctuations of the most input variables.

D.6.1. THE SOBOL INDICES

In this subsection, the first-order (S1), second-order (S2) and total (ST) Sobol indices to estimate the contribution of each input on the variance within the selected output variables. For this analysis, a 95% confidence interval is used for the estimation of every index. Table D.1 to table D.3 show the Sobol indices in table form.

	ST	ST_conf	S1	S1_conf
random-seed	0.009509	0.003264	0.005728	0.025988
NumStudents	0.480053	0.152283	0.401580	0.187431
Similarity_Threshold	0.605507	0.207347	0.522227	0.233792
PercBike	0.000066	0.000031	-0.000507	0.002077
PercCar	0.000066	0.000031	-0.000087	0.002265
Influence	0.000045	0.000015	-0.000206	0.001975
Sat	0.000035	0.000013	0.000590	0.001591
BeliefUpdate	0.000033	0.000011	-0.000396	0.001575

Figure D.4: Sobol indices in table form for all input variables with respect to the average size of reference groups

	ST	ST_conf	S1	S1_conf
random-seed	0.107499	0.066011	0.065535	0.088304
NumStudents	0.396025	0.150210	0.247989	0.193995
Similarity_Threshold	0.438441	0.212480	0.268760	0.151411
PercBike	0.004672	0.002269	-0.009627	0.024828
PercCar	0.004617	0.004466	0.001749	0.022354
Influence	0.065826	0.029972	-0.017736	0.076653
Sat	0.001140	0.000416	-0.001330	0.010870
BeliefUpdate	0.521272	0.209384	0.301933	0.160747

Figure D.5: Sobol indices in table form for all input variables with respect to the average change in belief-points for every evaluation

A clearer overview of these values in the tables is visualised and shown in figure D.7 to D.9. The total (orange bars) and individual (blue bars) contribution of the input variables on output variance have been visualised. As can be seen, the most contributing input variables differ per output variable. The y-scale refers to the percentage of contribution to the total variance in output when accounted. A few things stand out. First of all, the number of students seems to have a large first and higher order influence on all output variables. Furthermore, the increase or decrease in satisfaction levels, percentage of bike owners and percentage of car owners seem to contribute very little to nothing to output variance and thus are not a big cause of model uncertainty.

The black lines intersecting the orange bars (ST) and the blue bars (S1), represents

	ST	ST_conf	S1	S1_conf
random-seed	1.848509e-02	9.552197e-03	0.005911	0.042311
NumStudents	5.121443e-01	1.796050e-01	0.227970	0.224702
Similarity_Threshold	5.884345e-01	2.165214e-01	0.490203	0.192660
PercBike	0.000000e+00	0.000000e+00	0.000000	0.000000
PercCar	0.000000e+00	0.000000e+00	0.000000	0.000000
Influence	5.077713e-09	1.180637e-08	0.000014	0.000033
Sat	0.000000e+00	0.000000e+00	0.000000	0.000000
BeliefUpdate	0.000000e+00	0.000000e+00	0.000000	0.000000

Figure D.6: Sobol indices in table form for all input variables with respect to the average amount of students influenced

the ST_conf within the table. In other words, the larger this black stripe, the broader the confidence bounds of this Sobol index. As can be seen from figure D.7 to D.9, the confidence bounds are quite broad within this sample size. Because of this, a more sophisticated visualisation in order to examine the interaction between input variables has been computed.

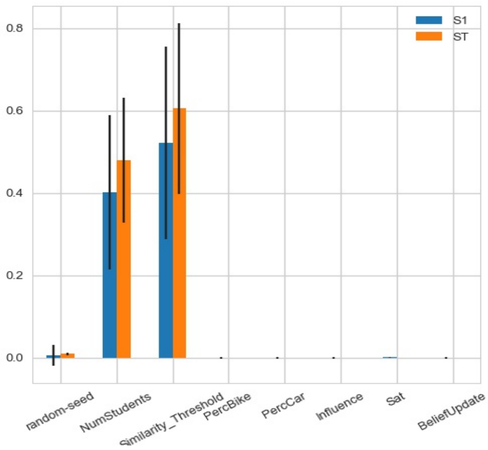

Figure D.7: Sobol indices visualised form for all input variables with respect to the average size of reference groups

Figure D.10 to D.12 give a clear overview on how input variables influence each other. In other words, how input variable A influences input variable B, which in its turn influences the output variable. The grey lines between input variables in D.10, D.11 and D.12 shows to what degree input variables influence each other. A thicker line indicated a stronger interaction between the input variables. The size of the black circle indicated the individual contribution of the input variable on the respective output variable. The white circle indicates the higher order effects of the input variable on variance in the respective output variable. Because of this, the black circle can never be larger than the white circle. Also; a strong influence line between input variables and a relatively large white circle when compared to the black circle, indicates that the largest part of influence contributed by this variable is caused by the connected variables and not through direct

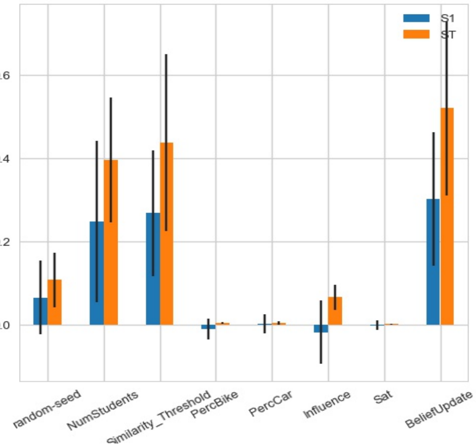

Figure D.8: Sobol indices visualised for all input variables with respect to the average change in belief-points for every evaluation

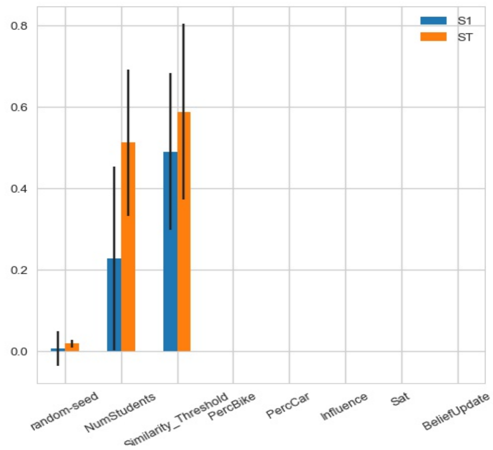

Figure D.9: Sobol indices visualised for all input variables with respect to the average amount of students influenced

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influence. An example of such an input variable can be seen in figure D.11, where the input variable "BeliefUpdate" nearly has no individual contribution to its caused variation in the average size of reference groups. The variance seems mainly to be caused by connected input variables "NumStudents" and "Similarity_Threshold".

From figure D.10 to D.12 can be deducted that from all analysed output variables, variance in the average change in beliefs are influenced the most by input variables. The variance in the sizes of reference groups and the share of students that are influenced are only caused by two input variables: the similarity threshold and the number of students. Therefore these output variables are relatively stable and does not cause a lot of uncertainty within the model.

Furthermore, the random seed seems to have quite some influence on the size of reference-groups and shift in belief-points. Therefore, no matter how certain the values given to the input-variables, the model will always carry a certain level of uncertainty.

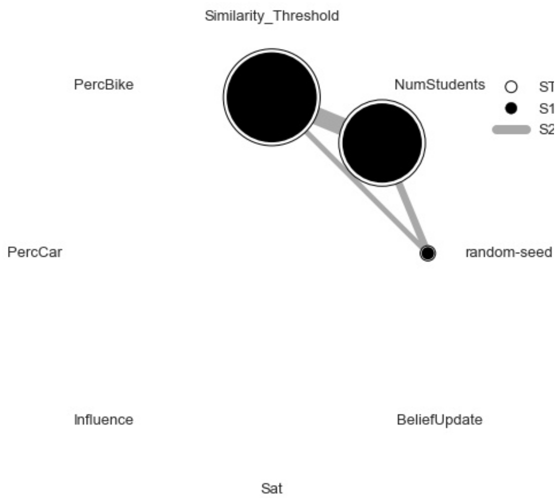

Figure D.10: Individual influence, higher order influence and interaction between input variables on the average size of reference groups

Now there will be taken a closer look at the output variable "Average belief change per evaluation", which seems to vary the most as a result of input variable variance. There can be seen from figure D.11 that besides the number of students, the similarity threshold and the amount of points agents update their beliefs are very influential variables. In figure D.2, there has already been shown that the variables "Similarity_Threshold" and "BeliefUpdate" are relatively strong correlated to the output variable of average change in beliefs. This means that a large individual contribution to variance of the output variable will actually have an effect on this output variable in the model. The input variable "Influence" also appears to have a large ST in figure D.11, but seems to be just very slightly correlated to the output variable when looked at D.2. Moreover, D.11 shows an almost entirely white circle for this input variable, indicating that the contribution it has to a variance in the output variable, is mainly caused by another variable. In this case, this would be the input variable "BeliefUpdate". It does not come as a surprise that these input variables are connected, as it is logical that the average shift in belief points from one evaluation is dependent on the degree to which students adjust their beliefs to the beliefs of others during one belief-update moment. Besides this interaction, there is also a strong connection between the similarity threshold and the belief update input variable. These are the three large influential input variables, that cause other variables to vary and contribute to the variance in average belief shifts per evaluation as well. Thus, variance within this output variable is mainly subjected to these three input variables, which also have the ability of strengthening or weakening each others value. This makes this output variable more uncertain, and with this output variable also the model.

In conclusion, there can be stated that many input variables contribute to variance in the output variables "average size of reference groups" and "average change in beliefs in points per evaluation". As is stated at the beginning of this chapter, special interest

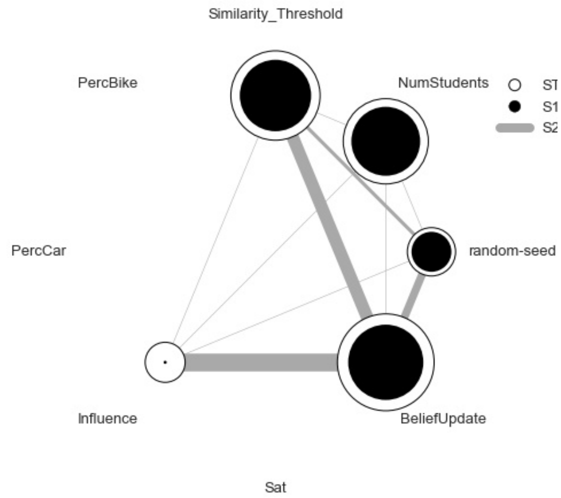

Figure D.11: Individual influence, higher order influence and interaction between input variables on the average change in belief-points with every evaluation

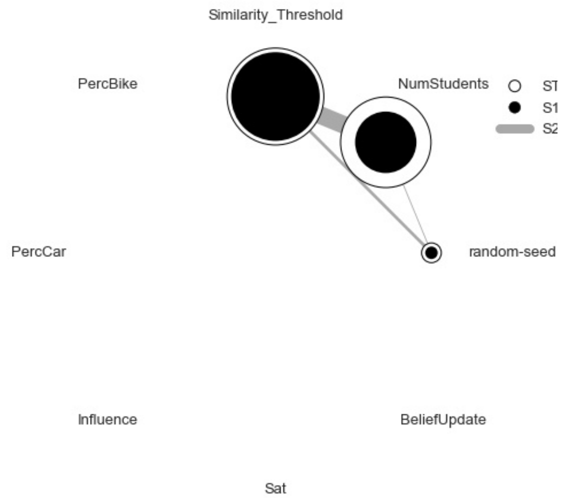

Figure D.12: Individual influence, higher order influence and interaction between input variables on the average share of influenced students

has been given to category 2 input variables, e.g. the variables which can vary in input value not only because they differ per case, but also because little it known about the exact values. The category 2 variables have been identified to be the input variables "Influence", "Sat", "Beliefupdate" and "Similarity_Threshold". From this analysis, we can conclude that all of the mentioned input variables of category 2 contribute significantly to variance in the output variables. Especially the similarity threshold and the degree to which agents shift their own beliefs to the beliefs of others in one single update moment are of big influence on output variance. This stresses the importance of correct inputs, which at this moment cannot be guaranteed. This is important to keep in mind when using the results of this model, and is further explained in chapter 9 of this thesis.

D.7. SENSITIVITY ANALYSIS OF THE MODEL WITH A RESTRICTED INFORMATION TRANSPARENCY BECAUSE OF DIFFERING THEORY OF MIND CAPACITIES OF AGENTS

For the model where agents do not have full insights into the cognitive system of other agents, the same sensitivity analysis has been performed. There has been added one input variable to this sensitivity analysis; the average miss estimation that agents have when estimating the beliefs of others. This variable differs from 0.1 up to 4 points. Fir this analysis, again the Pearson correlation coefficient between input variables and the three selected output variables are presented first. After this, the Sobol indices of all input variables are presented. Lastly, the interaction between input-variables is presented.

D.7.1. PEARSSON CORRELATION COEFFICIENT

Figure D.13 to D.15 show the Pearson correlation coefficients (r) for every input variable and output variable combination. As can be seen from figure D.14, there is little to no correlations found between all input variables and the output variable "Average change in beliefs", in contrast to the model with complete information transparency where this turned out to be the most sensitive variable. A reason for this might be found in the fact that belief-forming of agents is subjected to more uncertainty in the ToM-model, and will fluctuate more over time per definition. Subsequently, this fluctuation might be harder to influence through input variables than belief dynamics that are following one vast pattern. For this reason, this output variable will be left out of scope for the rest of the sensitivity analysis for this model. The average size of reference groups and the average share of influenced students are both vastly influenced by the number of students present in the model and the similarity threshold, just as in the model with full information transparency. Besides these input variables, these two output variables are also sensitive to changes in the input variable "Mean_deviation". In conclusion, the average size of reference groups and the average share of influenced students are both output variables with strong enough correlations with multiple input variables to be subjected to the rest of this sensitivity analysis.

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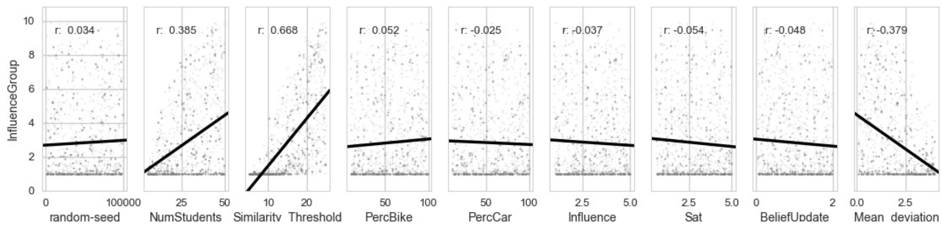

Figure D.13: Pearson correlation between input variables and the average size of reference groups in the ToM model

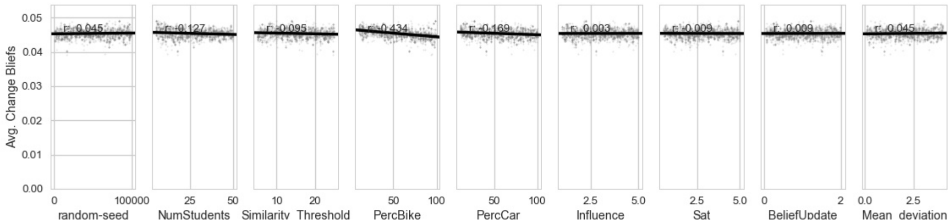

Figure D.14: Pearson correlation between input variables and the average change in beliefs during each evaluation process in the ToM model

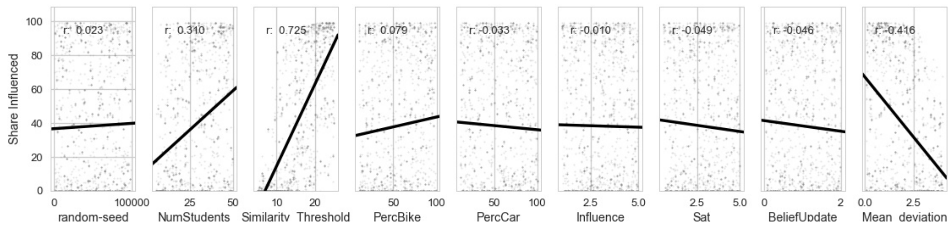

Figure D.15: Pearson correlation between input variables and the average number of socially influenced students in the ToM model

D.7.2. THE SOBOL INDICES FOR THE TOM OUTPUT VARIABLES

-At this moment, the graphics of blue and orange bars are not shown for this part in the sensitivity analysis because of limited time and relative little contribution to the conclusions. This will be added for the final version-.

Figure D.16 and D.17 display the contribution of input-variables to variance in the output variables. As can be seen, for both output variables the conclusion is that the similarity threshold, number of students and the mean of the mean deviation that students have when estimating others beliefs are the most influential for output-variance. As is discussed in section 2, a special interest goes out to çategory two'input variables, which already are fairly uncertain in nature and are not determined by the scenario. This leaves the input variables "Similarity Threshold" and "Mean deviation"to be the variables of interest. From the Pearsson correlation test there was already concluded that these variables are relatively strong correlated to the respective output variables, leading to these variables to have an influence of the actual output in a not to be overseen manner.

In conclusion, the sensitivity analysis for the theory of mind model presents the output variables "Average size of reference-group" and "Share of influenced students" to be the most sensitive output variables of interest, with the input variables "Similarity threshold" and "Mean deviation" to have the largest contribution to this uncertainty.

D.8. CONCLUSION

In conclusion, the model with and without full information transparency both have very different in- and output variables which contribute to their sensitivity. This difference in sensitivity can only be a result of a difference within the social comparison processes of

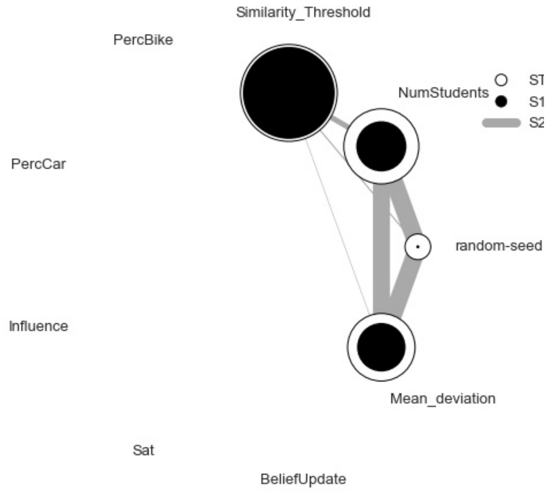

Figure D.16: Sobol indices visualised form for all input variables with respect to the average size of reference groups for the ToM-model

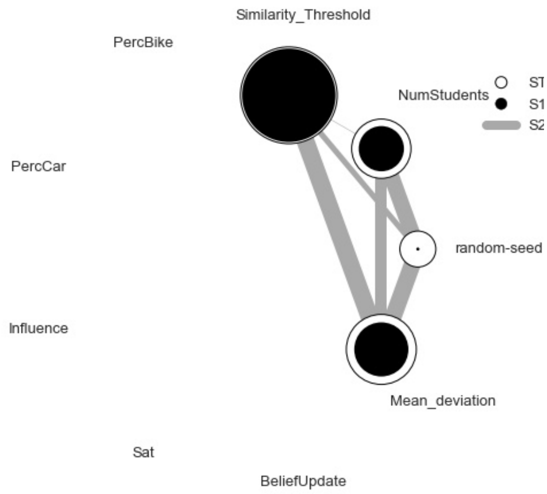

Figure D.17: Sobol indices visualised for all input variables with respect to the average amount of students influenced for the ToM-model

the models.

APPENDIX E: MODEL OUTCOMES

In this appendix, all simulation results are presented and described. First the results of the reference run are presented, followed by the results of the experiments. The car and fun belief relation is taken as an example to show in the figures, but for each value - transport mode combination experiments have been conducted and similar results have been found.

E.9. REFERENCE RUN RESULTS

First of all, figure E.18 presents the opinion dynamics results for all mode-value combinations, resulting from simulations with full information transparency, under all initial parameter settings. These initial parameter settings are as follows:

- Group-size (20 students) [**17**]
- Share of bike-owners (75%) [**18**]
- Share of car-owners (10%) [**19**]
- Similarity threshold (14) [**20**]
  Similarity threshold means the maximum amount of points indicating value-importance that agents can think differently on and still see each other as co-oriented peers.
- Increment of influence-strength of relations between agents **[15]**
  Once agents can build a relation because of their perceived similarities, the degree to which the influence-strength of their relation increases depends on their prosociality. Table E.15 presents the initial values for these influence-strength increments.

		Prosocial of self		
		0	**1**	**2**
Prosocial of other	**0**	0	0	0
	1	0	0.25	0.5
	2	0	0.5	1

Table E.15: Influence-strength increment subjected to prosocialness

- Amount of belief-points agents shift towards their co-oriented peers (relation-strength < 25 : 0.005, relation-strength > 25 : 0.01, relation-strength > 50 : 0.05) [**16**].
- Prosociality (normal distribution with mean = 0.48 and sd = 0.42) [**8**]

- Beliefs about value-activity relations
  These initial beliefs depend on the travel type of a student and can be found in appendix 9.5. They are not completely determined by the travel type, as variations within certain boundaries give space for agents to find agents of another type co-oriented to themselves.

- Importance given to values
  Just as with beliefs, the importance attached to values is agent specific put is given direction by the travel type of a student. Exact values given to this variable can be found in appendix 9.5.

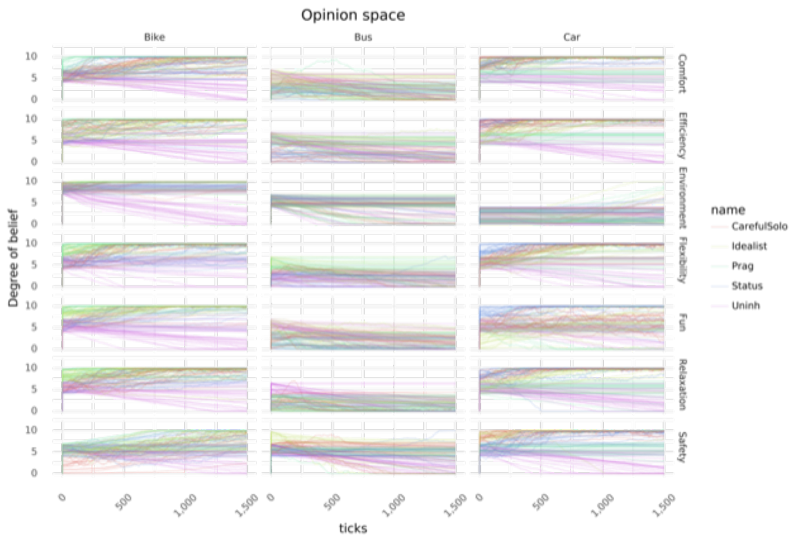

Figure E.18: Opinion dynamics for all mode - value combination, under fixed parameter settings for the full information transparency model

As can be concluded from this figure E.18, the beliefs of agents on transport mode - value relations shift over time and oftenly move towards one of the poles of the belief-space. This shift towards one of these poles is quite gradually, as most agents hold their beliefs at pole-level (either 0 or 10) once they reach this level. Besides moving to both sides of the poles, there also remain some zealots, leading to seemingly divergent beliefs. To zoom in on one particular belief dynamic, the bus as a transport mode and its relation towards different values in the opinion of agents can be analysed. Bus-value relations capture a larger belief field, but are spread less as they are often accumulated at the poles of the belief-ladder. Where beliefs about value relationships with car and bike activities are shifted towards both sides of the belief space, but bus-beliefs remained at the lower side of the belief-ladder. An explanation of this can be that most student travel types, have low **initial belief**s about value-bus relations, which can be seen as a relatively negative view on public transport. Because of these low beliefs in all value-bus relations, when a specific value is activated and the decision is made from reasoning from this specific value, the chance is big that when the agent chooses for the bus because of a lack of other options (due to affordances/competences), the evaluation will result in negative travel-satisfaction. Besides this, there are no other students who start with high bus-value beliefs and can influence others to move towards the higher belief-range. Hence, the restraint bus-beliefs on the lower side of the belief space.

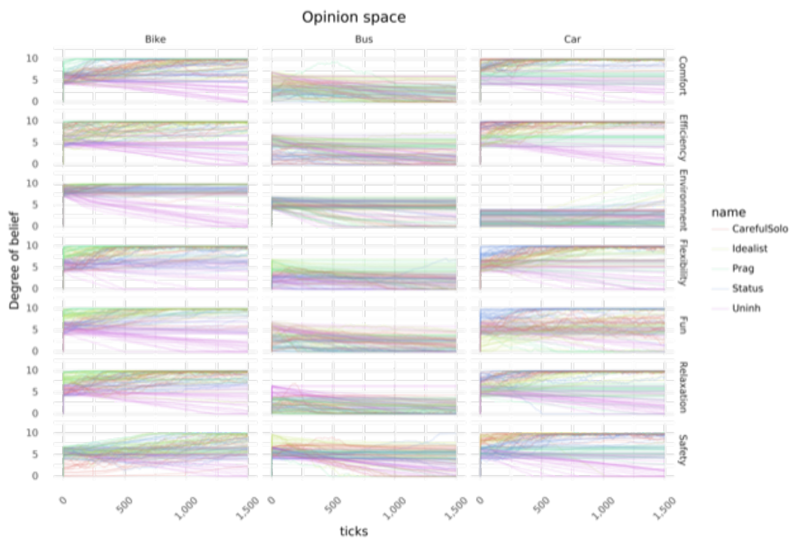

Figure E.19: Opinion dynamics for all mode - value combination, under fixed parameter settings for the ToM-restricting information transparency model

Subsequently, as can be seen from figure E.19, opinion dynamics are slightly different when ToM-capabilities are introduced. As can bee seen, just as with full information transparency there are many agents whose beliefs shift to either sides of the belief-space pole. When both opinion dynamics results are translated to a heat map this difference becomes more clear. Figure E.20 shows a heat map of the beliefs on the relation between the value fun and the car for both model versions. As can be seen from figure E.20, the ToM-model produces less polarisation, as more beliefs remain constant at belief-values that are not 0 or 10. This can be explained by the fact that less agents are socially influ-

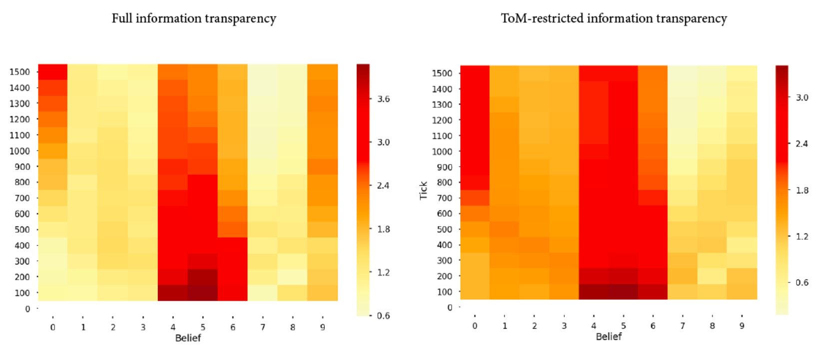

Figure E.20: Opinion dynamics for the car - fun belief combination, under fixed parameter settings for both model versions

enced and the agents who are socially influenced make mistakes in predicting the beliefs of others. To explain this last reason for less polarisation; in the ToM-model agents often shift their beliefs to the direction of what they think the beliefs of their co-oriented peers are, but what turns out not to be the case. Than, in the next belief-update step this belief adaption can be in the complete opposite direction, but this might also be a misinterpretation of other agents' belief-signals. In short, the belief adaption process is less linear than within the model with full information transparency.

E.10. EXPERIMENT RESULTS

Within the experiments, there is varied with the number of students present in the model and the similarity threshold. First the results for the model with full information transparency are presented, followed by the model with ToM-restricting transparency.

FULL INFORMATION TRANSPARENCY

These variances are done while all other parameter settings are kept constant as in the previous section is described. Figure E.21 displays the opinion dynamics for different numbers of students present in the model (5 to 40 agents). As can be seen from the results from this experiment, the more agents present in the simulation, the more beliefs are adapted and shifted towards one side of the belief-space pole.

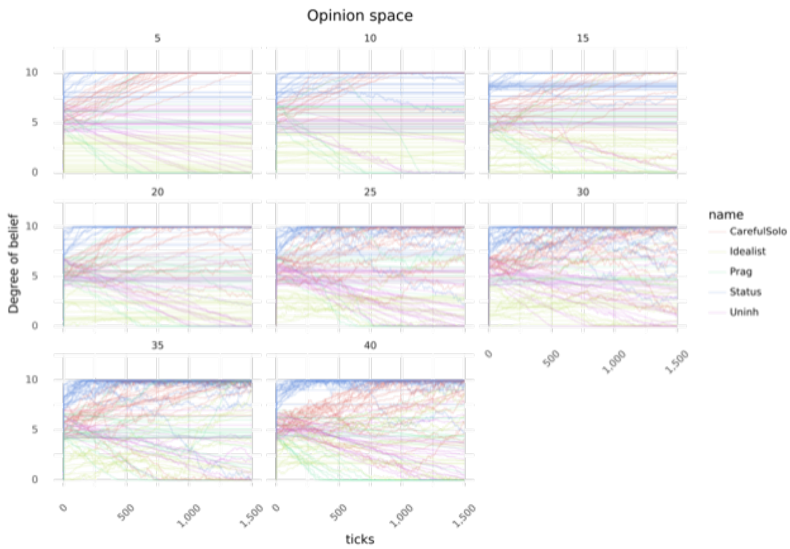

Figure E.21: Opinion dynamics with varying group sizes, for the full information transparency model

This statement is supported by the heat map shown in figure E.24, where the poles turn darker as the number of students go up, meaning that there higher share of students with this "extreme" belief when there are more students present in the simulation. For plotting the heat maps, the share of students with a certain belief has been used instead of the number of students, as the colours should indicate the same output and with 40 agents presents in the model, the number of students with a certain belief will automatically be higher. This would intervene with the message ought to substract from the heat map.

Figure E.23 shows the different opinion dynamics under varying similarity thresholds

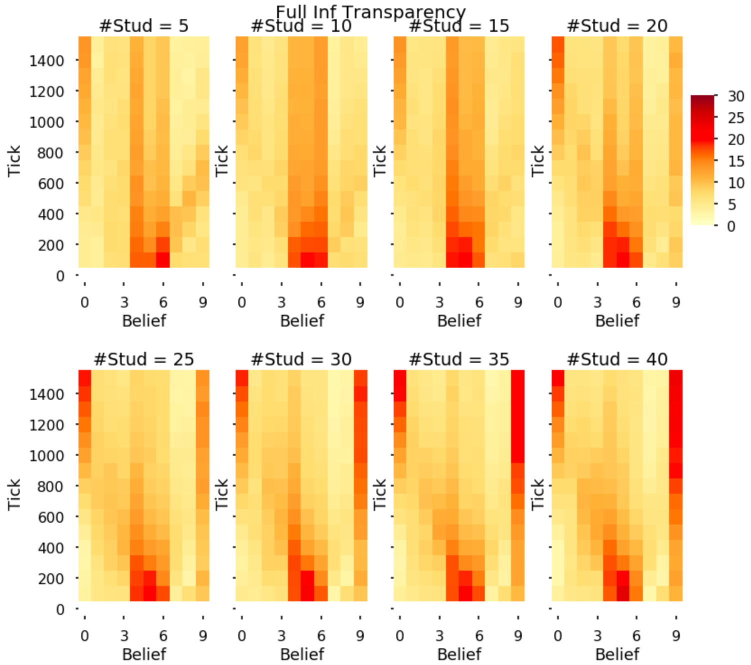

Figure E.22: Heat map of #students within belief compartment, under varying group sizes, for the full information transparency model

for the model with full information transparency. As can be seen, just as with the higher number of agents present in the model, also with a higher similarity threshold agents tend to shift their beliefs more often towards the poles of the belief space. This means that when agents find each other more quickly to be co-oriented peers, beliefs will shift more easy and more often towards the poles.

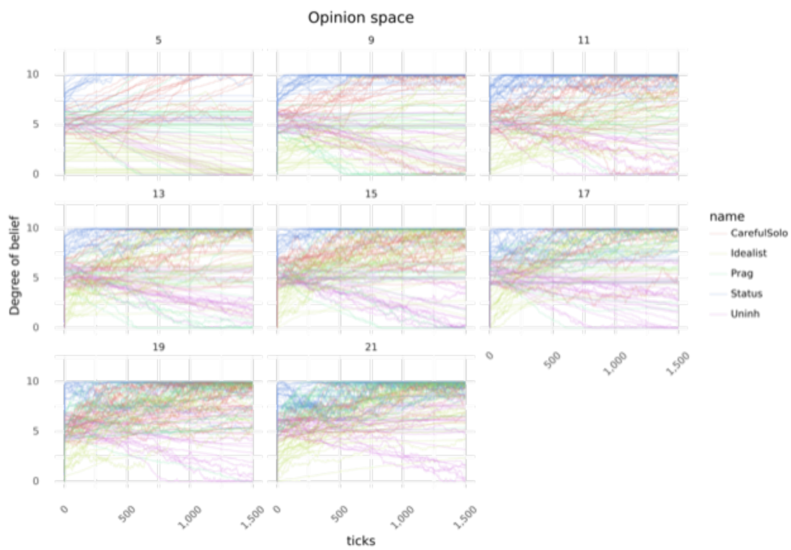

Figure E.23: Opinion dynamics with varying similarity thresholds, for the full information transparency model

The heat map in figure E.24 supports this finding.

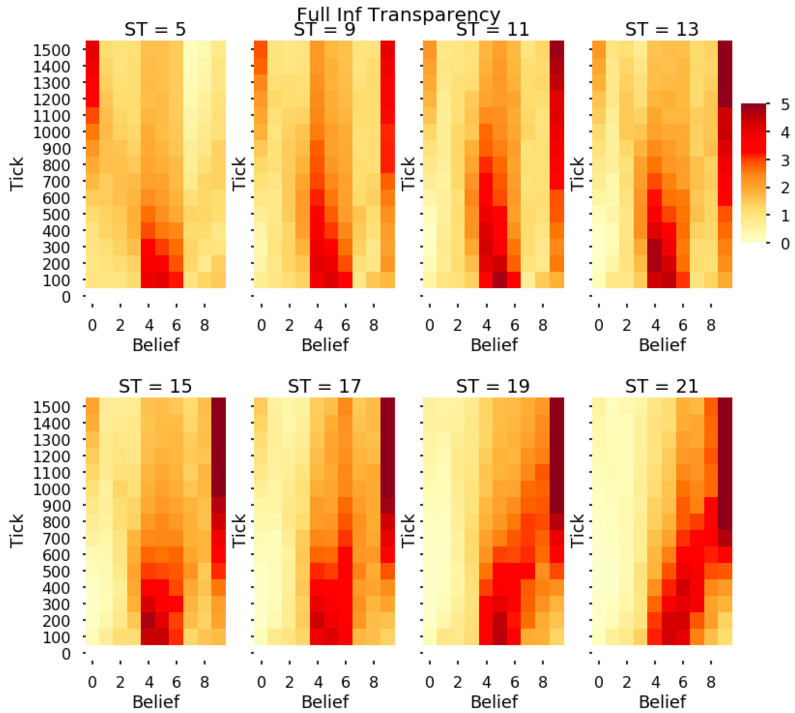

Figure E.24: Heat map of #students within belief compartment, under varying similarity thresholds, for the full information transparency model

ToM-RESTRICTING INFORMATION TRANSPARENCY

For the ToM- restricting information transparency model the same experiments have been conducted. Figure E.25 shows the opinion dynamics for varying amount of agents present in the simulation. As can be concluded from figure E.25, there are more beliefs that diverge towards the poles of the belief space as the number agents present in the simulation increase. However, this could also be an artefact of having more beliefs present in the simulation to begin with. Therefore, the heat map shown in figure E.26 needs to be consulted. This heat map shows that the clustering of beliefs is not significantly stronger as the number of students increase.

For the ToM-model there has also been analysed what the effect on opinion dynamics is for varying similarity thresholds. As can be seen in figure E.27, it can not convincingly be argued that more or less beliefs shift and cluster as the similarity threshold increases. When these effects are analysed in the heat map in figure E.28, there can be concluded that there is indeed no direct affect in opinion dynamics with an increasing similarity threshold for the model with ToM-restricting information transparency.

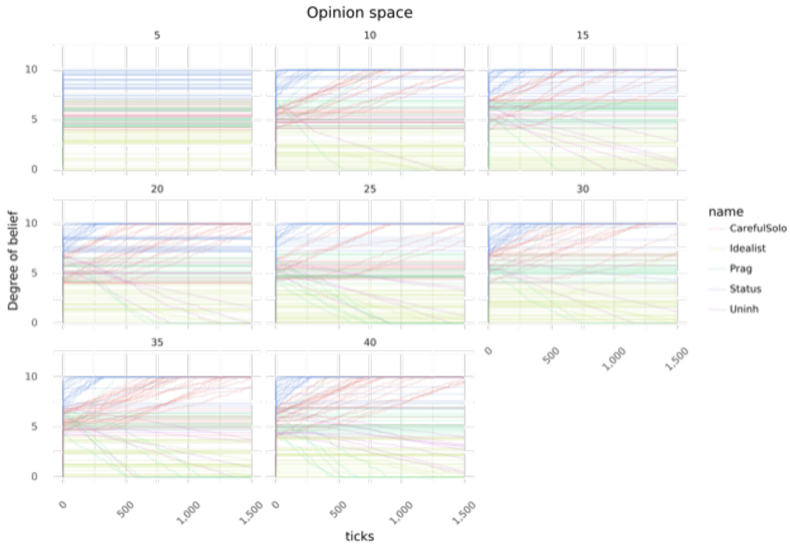

Figure E.25: Opinion dynamics with varying group sizes, for the ToM-restricting model

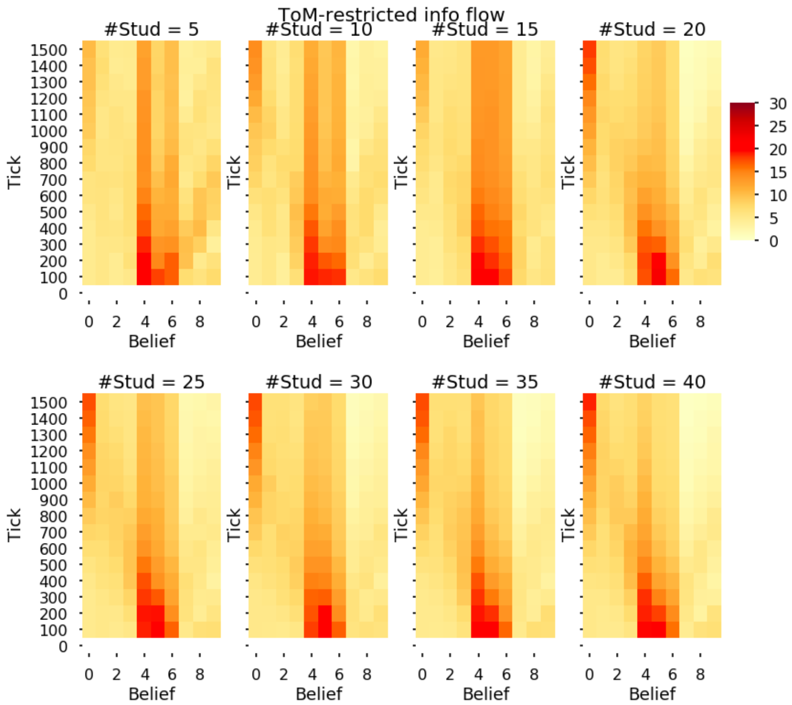

Figure E.26: Heat map of #students within belief compartment, under varying group sizes, for the ToM-restricting model

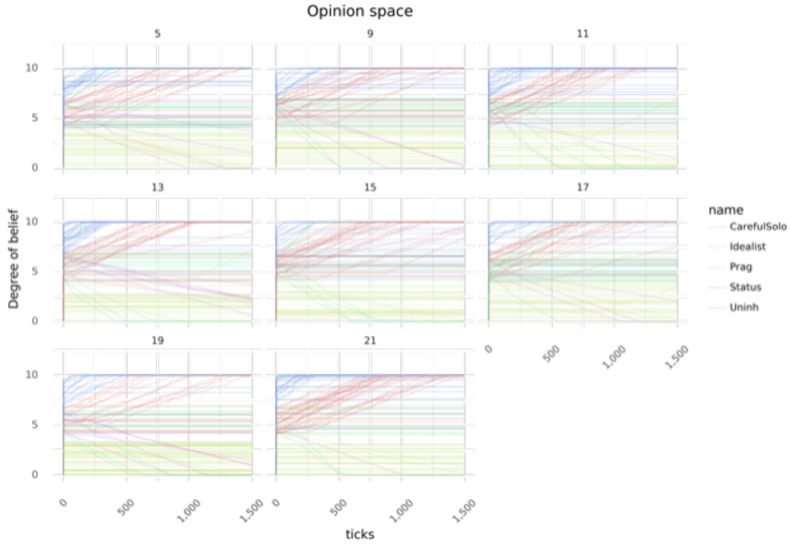

Figure E.27: Opinion dynamics with varying similarity thresholds, for the ToM-restricting model

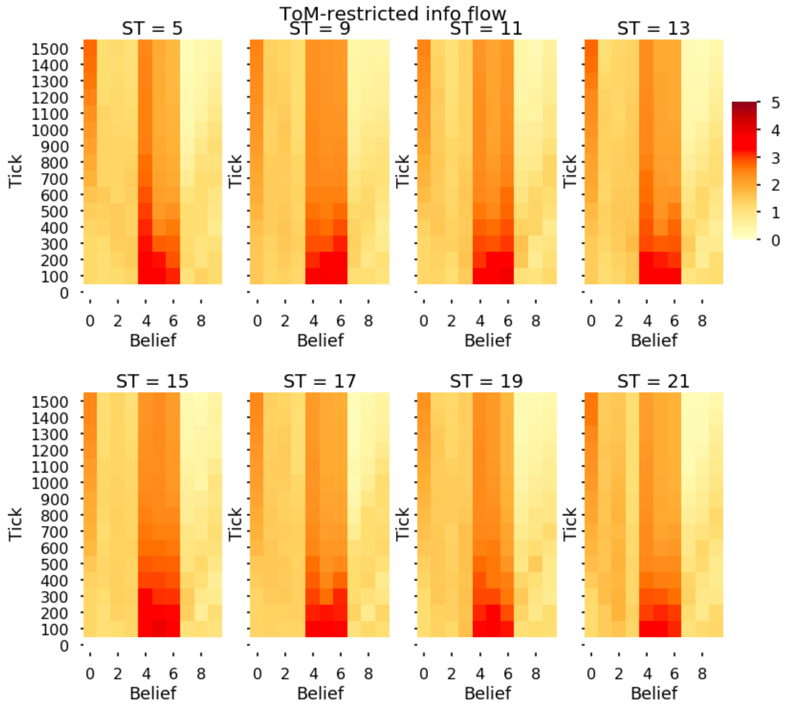

Figure E.28: Heat map of #students within belief compartment, under varying similarity thresholds, for the ToM-restricting model

E

Appendix F: Software and packages

This chapter provides an overview of software and packages used within this study. As versions of these tools and packages will change, possibly leading to incompatibility between the files presented for this thesis and the most up to date versions of tools and packages. In this chapter, the packages used for general purposes such as data modification and visualisation is not included.

Program	**Version**
NetLogo	6.0.4
Anaconda Navigator	1.9.7
Python	3.6.8

Package	**Version**
PyNetLogo	0.3

All associated codes and models have been made available through `https://github.com/nenaroes`.