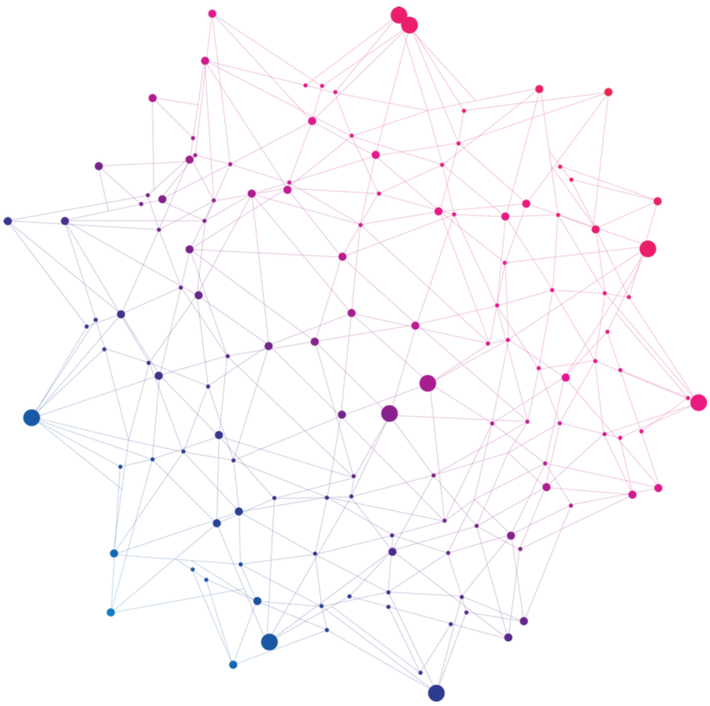
An Agent-Based Social Simulation Model of Belief System Change Applied to the Formation of Consumer Attitudes Towards Clean Energy Technologies



Kurt Harmen Kreulen
Master of Science (MSc) in Industrial Ecology
Leiden University: s1998633
TU Delft: 4695380

November 8, 2019

1st Supervisor:
Dr.ir. I. (Igor) Nikolic
Technical University of Delft
Faculty of Technology, Policy and Management:
Multi-Actor Systems (Systems Engineering)

2nd Supervisor:
Prof.dr.ir. I.R. (Ibo) van de Poel
Technical University of Delft
Faculty of Technology, Policy and Management:
Values, Technology and Innovation (Ethics and Philosophy of Technology)

Partner:
T. (Ton) Wurth
Business Development Professional at Siemens Smart Infrastructure

Universiteit Leiden
Science

TU Delft
Delft University of Technology

An Agent-Based Social Simulation Model of Belief System Change Applied to the Formation of Consumer Attitudes Towards Clean Energy Technologies

Master thesis submitted to Delft University of Technology
in partial fulfilment of the requirements for the degree of

MASTER OF SCIENCE
in **Industrial Ecology**

Institute of Environmental Sciences (CML)
Faculty of Science, Leiden University

by
Kurt Harmen Kreulen
Student number (Leiden University): s1998633
Student number (TU Delft): 4695380

To be defended in public on
12-11-2019, 12:00
at TU Delft Faculty of Technology, Policy and Management.

Graduation committee:

First Supervisor:
Dr.ir. I. (Igor) Nikolic
Technical University of Delft
Faculty of Technology, Policy and Management:
Multi-Actor Systems (Systems Engineering)

Second Supervisor:
Prof.dr.ir. I.R. (Ibo) van de Poel
Technical University of Delft
Faculty of Technology, Policy and Management:
Values, Technology and Innovation (Ethics and Philosophy of Technology)

Partner:
T. (Ton) Wurth
Business Development Professional at Siemens Smart Infrastructure

~ Statement of Originality ~

This document is written by **Kurt Harmen Kreulen** who declares to take full responsibility for the contents of this document. I declare that the text and the work presented in this document is original and that no sources other than those mentioned in the text and its references have been used in creating it.

Acknowledgements

This thesis constitutes my completion of the master's programme Industrial Ecology, thereby concluding my time at the Delft University of Technology and Leiden University.

First of all, I would like to call out a big "thank you!" to my supervisors Igor Nikolic and Ibo van de Poel.

Igor, during our meetings you never ceased to inspire me with your sharp and creative thinking. Your ideas and feedback were enormously helpful and interesting. Your friendly support and encouragement enabled me to create a full-fledged agent-based social simulation model; something I did not think I was capable of during the onset of writing this thesis.

Ibo, I am grateful to have been able to discuss my thoughts with you during the past months. Your critical and constructive feedback helped me reason and formulate my ideas more logically and concisely. Conversing with you was intellectually stimulating and I thank you for freeing up the time to do so!

To both of you, I would strongly recommend you to any graduate considering writing on a thesis topic affiliated with one of your areas of expertise. May our paths cross again in the future ☺

I would like to conclude by thanking my family and girlfriend for their loving support.

Executive Summary

Nations across the globe are currently struggling to decrease the environmental impact of their energy systems. Even though the irrefutable evidence for anthropogenic climate change has been publicly available for several decades (Le Treut et al., 2007), the need for a great energy transition has only come to be a priority for national governments in recent years. An explanation for this observation is that people have come to ascribe a higher value to environmental sustainability over the past few years. Hence, the great energy transition may be framed as the struggle to incorporate the value of environmental sustainability into the current functioning of national energy systems.

Conceptualizing, understanding and potentially anticipating particular forms of value change may help to preclude having to make costly modifications to energy systems in response to collective shifts in people's values. This study therefore aims to identify and conceptualize the mechanisms that underpin value change within an energy system's context.

The focus of this study lies specifically on conceptualizing how values, and their respective change, affect consumer decisions to adopt Clean Energy Technologies (CETs). Broad trends in the consumer adoption of CETs drive the bottom-up sustainability transformation of the energy system (Rai & Henry, 2016). To enrich our understanding of this phenomenon, an agent-based model is constructed that is able to simulate the conceptualized value change process. This model is given the name "Energy Consumer Belief Change Simulator" (ECBCS).

The purpose of the ECBCS is to investigate how the various mechanisms that characterize the conceptual model of value change interact to generate certain classes of outcomes, and to specify the conditions under which they do so. This modelling purpose is referred to as *theory exposition* (Edmonds et al., 2019). Hence, the ECBCS is not built with the aim of *explaining* or *predicting* value change. To put it differently, the current study focusses on understanding the behaviour of the model *itself*, rather than making any claims about value change in real societies. Nonetheless, a brief reflection is provided on how some of the outcomes generated by the ECBCS correspond to belief change related phenomena observed in the real world. The reason for doing this is to assess the usefulness of the ECBCS for potentially informing more elaborate, evidence-based explanatory models of value change.

Lastly, this study takes a critical look at the usefulness of ABMs in terms of their ability to help researchers systematically test and improve upon theories that aim to explain value change.

To summarize, this study aims to provide a comprehensive answer to the following research question:

"How can belief system change and the formation of energy consumer attitudes with regards to clean energy technologies be conceptualized, and can this conceptualization be formalized and studied using an agent-based modelling approach?"

It is found that value change is inherently related to belief system change. Values are affectively-laden beliefs that interact with knowledge, or factual beliefs, to form attitudes. Knowledge consists of mental convictions about how the world is (facts) and values represent mental convictions about how the world ought to be. Attitudes can be thought of as the evaluation of an object or entity (e.g. an energy technology) that is formed on the basis of a collection of values and factual beliefs. It is proposed that a change in values and/or factual beliefs, or belief system change, leads to a change in attitudes which in turn affects a consumer's decision to adopt a CET.

Belief system change is found to be a complex multi-level process that is heavily influenced by socialization and culturalization. On a micro-level, an individual's beliefs may change as a result of introspective contemplation that can be triggered by a direct exposure to certain classes of events. To illustrate, a person that firmly believes "all swans are white" will experience rapid belief change upon perceiving a black swan. This example serves as an analogy to describe how exposure to novel and surprising information may prompt someone to revise her beliefs.

On a meso-level, beliefs are shaped by social interaction and exposure to media. During social interaction, people may influence each other's values through processes of persuasion and emotional contagion. People may also exchange factual information that help them acquire a more accurate understanding of how things in the world are related and what the consequences of particular actions are. Furthermore, people may be exposed to mediated information which can, under certain conditions, exert a significant influence on the content and configuration of their belief system.

On a macro-level, beliefs are shaped by culture. Humans are innately predisposed to follow and enforce cultural conformity. Culture can be thought of as the belief system of a society of social group. It is proposed that the change in a person's beliefs tends to be biased in favour of the cultural standards that she is aware of.

Upon testing the conceptualization of belief and attitude change using the ECBCS, various regularities were observed with regards to the model's behaviour. Some of which are:

- The emergence of no more than three well-define clusters of like-minded agents;
- A pattern of value change characterized by a global consensus around a viewpoint of indifference;
- A pattern of value change characterized by a collective drift in viewpoints towards extremity;
- A pattern of value change characterized by a polarization of viewpoints;
- A smaller disagreement in the attitudes that agents hold with regards to various CETs than in their value-related viewpoints.
- A higher degree of consensus in agent attitudes towards electric vehicles (EVs) than in their attitudes towards photovoltaic-cells (PVs) and heat pumps (HPs);
- A positive effect of perceived system instability on values related to self-enhancement and conservation. Inversely, system instability negatively affects values related to self-transcendence and progression.
- A polarizing effect of media on agent value-related viewpoints.

A subset of these regularities is interpreted in terms of their correspondence to belief change related phenomena observed in the real world.

Based on the author's experience with constructing and testing the ECBCS, it is concluded that ABMs can be useful tools for systematically studying belief system change within an energy system's context. It is found that the suitability of ABMs is contingent upon the characteristics of the research context in which they are deployed. These characteristics refer to *inter alia* the promotion of inter-scientist collaboration, long-termism, interdisciplinarity, and the construction of evidence-based models that 'learn' from the mistakes of other models.

Keywords: *belief system change, value change, attitude change, energy consumer behaviour, clean energy technology adoption, innovation diffusion, energy transition, sustainability, computational modelling, agent-based modelling, agent-based social simulations, socio-technical systems, multi-actor systems.*

Abbreviations

Concept	Abbreviation
Active Agent	AA
Agent-Based Model	ABM
Agent-Based Social Simulation	ABSS
Attribute Performance	AttPerf
Attribute Performance Assessment	APA
Belief System Change	BSC
Clean Energy Technology	CET
Confidence Weight	CW
Electric Vehicles	EVs
Energy Consumer Belief Change Simulator	ECBCS
Factual Statement	FS
Heat Pumps	HPs
Internal-Combustion Engine Vehicles	ICEVs
Passive Agent	PA
Photovoltaic-cells	PV
Socio-Technical System	STS

Table of Contents

1 Introduction

This first introductory chapter consists of a problem analysis that clarifies the motivation for - and relevance of - writing this thesis. Subsequently, a detailed description is provided of the current research scope, questions, objectives and design.

1.1 Problem Analysis

1.1.1 Climate Change & Global Energy Challenges

Present-day industrial societies are strongly dependent on the availability of fossil fuels for energizing the mass-scale activities of production and consumption that characterize them (Unruh, 2000). A large body of scientific evidence points out that this wide-scale application of carbon-based energy technologies has been, and still is, a dominant cause of climate destabilization (Cook et al., 2013).

A non-exhaustive list of risks related to human-induced climate change are an increased threat of extreme temperature events, severe droughts, heavy precipitation, intensified storms, floods, ocean acidification and the emergence of new pandemics due to altered insect and disease patterns (Intergovernmental Panel on Climate Change, 2015). Anthropogenic climate change is highly problematic since humans across the globe depend on stable weather patterns and proper functioning ecosystems for growing nutritious food and maintaining healthy living conditions.

Besides the environmental impacts of widespread application of carbon-based energy technologies, there exists a long history of conflict and geopolitical tension related to nations' efforts of ensuring energy security and sovereignty in the face of a volatile and, over the long-term, dwindling oil supply (Dorian, Franssen, & Simbeck, 2006). Thus, in order for humanity to be able to thrive in the 21st century and those to come, it is vital that the global demand for energy is met through low- or zero-carbon technologies.

1.1.2 The Dutch Energy Transition

Concerns about fossil fuel depletion, dependency on foreign suppliers and climate change have led Dutch policymakers to ratify the Kyoto Protocol and Paris Agreement (Kemp, 2010). In doing so, the Netherlands has declared to contribute to limiting global warming to 2°C, and if possible to 1.5°C (van Vuuren, Boot, Ros, & Hof, 2017). As a consequence, the Dutch government will have to work towards drastically reducing the nations CO_2 emissions over the coming decades (van Vuuren et al., 2017).

It must be noted that CO_2 is not the only greenhouse gas (GHG) as methane (CH_4), nitrous oxide (N_2O), fluorinated gases and water vapor (H_2O) also play an important role within the context of anthropogenic climate change (Lashof & Ahuja, 1990). However, since CO_2 emissions represent 85% of total Dutch GHG emissions and almost all of it results from the operation of the Dutch energy system (van Vuuren et al., 2017), the focus of Dutch climate policy lies primarily on the development of a carbon-lean energy system. Households typically account for 15 to 20% of total energy-related CO_2 emissions in Western European countries (Abrahamse & Steg, 2009), highlighting the importance for Dutch governmental bodies and private parties to pay attention to anticipating and/or steering residential energy consumption behaviour.

1.1.3 *The Sustainability Transformation of the Dutch Energy System*

Fostering and managing the energy transition calls for a systems-oriented approach as advocated by the fields of complexity science and industrial ecology (Rotmans & Loorbach, 2009). Complexity science provides ways of analysing and understanding the behaviour of a complex adaptive system with the aim of steering its development towards a desired state (Rotmans & Loorbach, 2009). Industrial ecology provides a framework that helps to formulate such desired system states (Ayres & Ayres, 2002; Ehrenfeld, 2004)

The Dutch energy system comprises the totality of energy-related activities within the Netherlands ranging from extraction, refining, upstream generation, transmission, transportation, storage, and final consumption. The Dutch energy system is a socio-technical system (Chappin, 2011; Dam, Nikolic, & Lukszo, 2013; Geels, Sovacool, Schwanen, & Sorrell, 2017), which means that it is composed of two interconnected subsystems: *"...a social network of actors and a physical network of technical artefacts"* (van Dam et al., 2013, p. 1).

These two subsystems co-evolve with one another; that is, they evolve interdependently (Geels et al., 2017). This is illustrated by the fact that the actor network determines the development, operation and management of the technical system, which in turn influences the behaviour of the actor network (van Dam et al., 2013). Agents that comprise the actor network of the Dutch energy systems include, for instance: energy suppliers, traders, grid-operators, investors, governmental bodies, and consumers (van Dam et al., 2013; Verbong & Geels, 2007). The artefacts that constitute the technical subsystem are, for example: thermal power plants, off- and onshore wind facilities, solar cells, transmission lines, transformer stations and distribution networks (van Dam et al., 2013).

The laws governing the relationships and interactions between the technical artefacts are physical and absolute (e.g. thermodynamics and chemistry) (Meadows, 1997). The laws dictating the behaviour of the socio-subsystem are of a statistical (i.e. correlational) and more abstract nature; their study belongs to the realm of the social sciences (e.g. psychology, sociology). A key takeaway is to understand that it is insufficient to look at the energy transition from a singular perspective of 'hard engineering'; the psychological, social and cultural forces that are active within the system must certainly also be addressed (Chappin, 2011; Nikolic, 2018).

In addition to being socio-technically natured, energy infrastructures are highly complex (Chappin, 2011). Systems are considered to be complex when they contain a vast number of (social and technical) elements that interact with one another in a manner that is generally stochastic and non-linear (Rotmans & Loorbach, 2009). Moreover, all of these interactions occur in a parallel mode and are distributed across the entire system, which renders the making of precise causal inferences and accurate forecasts a futile endeavour (van Dam et al., 2013).

Shaping the complex evolution of energy systems requires one to step away from classical, or mainstream approaches to problem-solving. These approaches are generally characterized as being short-termist, palliative, linear and reductionist (de Witt, 2018). Instead, one might consider the theoretical notion of *leverage points*. Leverage points are places within complex systems where a relatively small shift in one thing may lead to fundamental changes in the system's overall functioning (Meadows, 1997).

Notably, the 'deepest' leverage points are to be found *not* within the physical part of the system, but within the minds of the actors that constitute the social subsystem. The deepest leverage points involve addressing 'the rules of the game', and/or the intent characteristics (i.e. *purpose*) of the system (Meadows, 1997). Changing the system's purpose relates to understanding and altering the dominant values and norms embedded within its functioning (de Witt, 2018).

From this perspective, 'problematic' or 'failing' systems may otherwise be understood as systems that function just fine, but that have emerged out of a purpose that a majority of people within society no longer supports (de Witt, 2018; Demski, Butler, Parkhill, Spence, & Pidgeon, 2015). The Dutch energy system, for instance, has evolved out of a purpose that can be expressed predominantly in economic terms (e.g. minimizing cost and maximizing yield of operations). From an economic perspective, then, it can be stated that the Dutch energy system is flourishing rather than failing. However, processes of value change within society over the past years have led to an increase in the importance ascribed to environmental sustainability (Demski et al., 2015). The current need for an energy transition can therefore be framed as the struggle to incorporate the value of environmental sustainability into the current design and functioning of the system (de Witt, 2018; Demski et al., 2015; van de Poel, 2018). Thus, understanding the energy challenges we currently face demands an understanding of why and how people's values change.

1.1.4 *The Coevolution of Values and the Physical Energy System*

The appraisal of an energy system can happen in a variety of ways depending on which performance dimensions receive attention. This allocation of attention is determined by the presence and prioritization (i.e. configuration) of values within people's *value systems* (Demski et al., 2015; Perlaviciute & Steg, 2015). Value systems are defined here as (hierarchical) networks of affective beliefs with regards to preferred end-states of reality (Antonides & van Raaij, 1998; Gärdenfors, 2005; Grube, Mayton, & Ball-Rokeach, 1994).

From a socio-technical perspective, the configuration of people's value systems affect, and are affected by, a system's technical functioning (see Figure 1). The energy system's operations impact the environment, which generates signals that can be picked up by the actor network (see Figure 1). When actors detect these signals, they can be measured, converted into data, interpreted and communicated (Matutinović, 2007b, 2007a). In doing so, actors are able to update their evaluations of the quality of the physical state, or technical functioning, of the energy system (see Figure 1).

Note, however, that the signals picked up from the environment are distorted by the way they are measured, interpreted and communicated. The quality of measurement depends on the technological capabilities of the actor network, and the quality of interpretation is contingent upon an actor's knowledge-base and the configuration of its value system (Matutinović, 2007b). Moreover, the quality of communication depends on an actor's intentions (e.g. agenda-setting and framing) (Weaver, 2007). Taken together, these processes extract *meaning* from information and are collectively referred to as the *system of interpretance* (Salthe, 2007). The intrinsic characteristics of the system of interpretance make it so that incoming information will generally be biased towards upholding the prevailing worldview (Matutinović, 2007b). This is illustrated by the fact that, up until now, mostly marginal and/or palliative technological and institutional changes have been implemented in response to environmental problems as opposed to more transformative measures (de Witt, 2018).

When actors believe the energy system is performing well, they are motivated to maintain the status-quo. When the system is believed to be failing, actors are pressed to react by allocating their efforts towards restoring a positive evaluation of the system. It is hypothesized that the level of discrepancy between how the system functions and how it *ought* to function, determines the scale and perceived urgency of the corrective measures to be taken by the actor network. These corrective measures include, for instance, institutional changes (Chappin, 2011; Matutinović, 2007b), wide-spread adoption of innovative (clean) energy technologies (Nordlund, 2009; Rai & Henry, 2016), altering one's energy consumption (or savings) behaviour, and protesting or voting against (or in favour) of some energy policy intervention (Moglia, Podkalicka, & McGregor, 2018; Poortinga, Steg, & Vlek, 2004); see Figure 1. The current study focusses on understanding how value change might affect the public acceptance and/or individual adoption of Clean Energy Technologies (CETs). CETs include, for instance, solar photovoltaic (PV) cells, battery electric vehicles (EV), and electric heat pumps (HP). These CETs enable consumers to reduce their carbon footprints and transform the physical state of the energy system from the bottom up.

The increasing importance ascribed to environmental values by consumers can be leveraged by enabling and stimulating residential investment in CETs. Based on the presumption that people generally feel the need to act in accordance with that which they perceive to be important or valuable in life (Bergman, 1998; Stern, 2000; Wilson & Dowlatabadi, 2007), it is expected that empowering consumers in the right ways should increase CET adoption rates (Wolske, Stern, & Dietz, 2017). Over an extended timeframe, such demand-side developments should send ripple effects through the energy system pushing its evolution towards a more energy efficient and less polluting state (de Wildt, 2017; Rai & Henry, 2016).

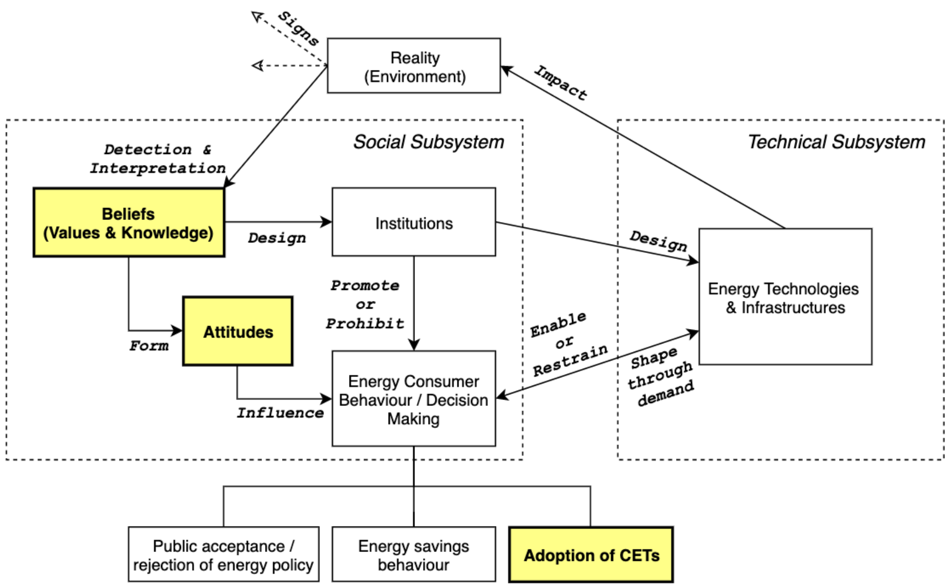


Figure 1. *Conceptual Model of Coevolution Between Values and Physical Energy System.*

Note: The scope of the current thesis is limited to the relationship between values and the formation of attitudes towards CETs; see highlighted variables in Figure 1. Specifically, it is presumed that values interact with knowledge to form attitudes, which in turn influence a consumer's decision to adopt a CET.

1.1.5 *A Modelling Approach to Understanding Belief System Change*

In recent decades, values have been changing faster than the energy system's ability to keep up with how it ought to function. Consequently, tension is building up between what is and what ought to be. It is hypothesized that this tension will keep on building up until the discrepancy between what is and what ought to be becomes so great that a sudden paradigm shift will take place in order to restore the balance (Gowdy, 1994; Rotmans & Loorbach, 2009). Punctuated overturns in a dominant worldview are a conflict-ridden and highly uncertain process (Matutinović, 2007b). Forestalling the occurrence of such destabilizing punctuations requires one to anticipate value change. Anticipation of value change enables one to manage the discrepancies between what is and what o ught to be throughout the lifetime of a socio-technical system (van de Poel, 2018). One approach to obtaining the ability to anticipate value change might be to simulate it.

As is described in more detail throughout Chapter #2, values influence behaviour through the interaction with one's factual understanding of reality. Specifically, values and knowledge form attitudes which, in turn, influence one's behaviour (Armitage & Conner, 2001). Values and knowledge are conceptualized as forming a *system of beliefs* that provides an individual with a sense of how the world is and should be, respectively (see Figure 2). Hence, value change is fundamentally related to belief system change.

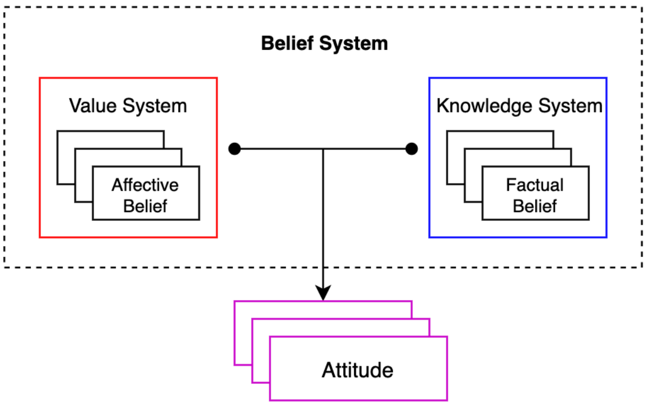


Figure 2. *Affective and Factual Beliefs Constitute Belief Systems.*

Recent advances in state-of-the-art modelling techniques enable researchers to build ever more sophisticated computer simulations of complex social phenomena (Li, Mao, Zeng, & Wang, 2008). These developments provide reasons to inspect whether belief system change can be studied using a computational modelling approach.

Computer models, together with mental and conceptual models, constitute ways of transmuting reality into abstract and simplified forms (Bollinger, Nikolić, Davis, & Dijkema, 2015). An important aim of models is to explain real-world phenomena and/or to grasp the complexity (or simplicity) inherent in a particular phenomenon (Epstein, 2008). Since models are (highly) simplified abstractions of reality, a lot of information is lost through the compression and filtering that takes place during a model's construction. This means that, although they can be useful, models are never *true* (Box, 1979). However, even though models are inherently flawed, it is arguably better to base strategic decision-making on the outcomes of *in silico* experiments than it is to blindly do things and hope that they will work out for the best (Nikolic, 2009).

If all possible future events were ascribed a uniform probability of occurring, the future would involve such enormous complexity that it would paralyze present-day strategic decision-making (Lewis & Weigert, 1985). Reducing this complexity to manageable proportions can be done by collecting and processing information about known, or theorized (causal) relationships (Lewis & Weigert, 1985). These relationships can be integrated into a conceptual model. The conceptual model may then be formalized and simulated using computer modelling techniques. In doing so, computer models may provide a better-informed, i.e. *posterior*, probability distribution of future scenarios, which then enables more purposeful decision-making.

A variety of computer modelling techniques can be applied to aid strategic decision-making within energy systems amongst which Computational General Equilibrium (CGE) models, System Dynamics Models (SDMs) and Agent-Based Models (ABMs) (Chappin, 2011; Nikolic, 2009). Modelling and simulating the process of value change requires a technique that is able to represent a population consisting of heterogeneous individuals that are able to interact and influence one another. Additionally, the modelling technique must be able to simulate how these factors play out on a micro-scale and create emergent outcomes on a macro-scale (Moglia, Cook, & McGregor, 2017). Essentially, the model must itself be complex enough to be able to represent the system's complexity as expressed by the notion of *requisite variety* (Ashby, 1991). Arguably, ABMs are best able to satisfy these prerequisites (Chappin, 2011; Köhler et al., 2018; Rai & Henry, 2016; Rai & Robinson, 2015; van Dam et al., 2013).

ABMs represent systems as collections of discrete decision-making entities (i.e. agents) that are able to interact with one another over varying temporal and spatial scales (Rai & Henry, 2016). ABMs enable one to build agents that exhibit a high variety of information processing and decision-making schemes and that can be programmed to have sophisticated personalities. In doing so, ABMs allow us to simulate and test comprehensive theories of human behaviour (Rai & Henry, 2016). These characteristics of ABMs provide reasons to assume that they may be able to offer us valuable insights into how values, knowledge and attitudes evolve under different scenarios.

Using ABMs to construct virtual worlds does not force the modeler to over-abstract a given target-system (Vermeulen & Pyka, 2016). This is because ABMs are bound only by the limits of algorithmic computation; in other words, ABMs are not constrained to be mathematically tractable (Galán et al., 2009; Nikolic, 2009). This aspect of ABMs forms a double-edged sword since it enables a researcher to potentially construct a very accurate representation of an actual real-world system, but it also increases the risk of losing oneself in irrelevant and/or distracting details. To illustrate, a road map should include the possibility of representing bicycle tracks; however, the ability to represent tree houses seems redundant. This risk is particularly pertinent in case a target-system is characterized by the presence of complex social phenomena (Edmonds, 2010; Galán et al., 2009; Vermeulen & Pyka, 2016).

Furthermore, modelling complex social systems requires dealing with, *inter alia*, extremely high degrees of freedom and *deep uncertainty*. Deep uncertainty refers to the difficulty of validating the conceptual models that delineate a system's components and the relations and interactions between them. It also refers to the difficulty of estimating the probability density functions that define the behaviour of parameters present within such models (Lempert, Popper, & Bankes, 2003). Deep uncertainty essentially refers to the difficulty (and sometimes impossibility) of formulating a response to the questions presented in Table 7 (Appendix 1).

In light of the foregoing, it seems relevant to gauge the usefulness of ABMs for studying belief change and related complex social phenomena. This study does so by critically reflecting on the disadvantages and the benefits of constructing ABMs to study belief change.

1.1.6 *Scientific Relevance of Thesis*

This thesis brings together modelling work done on attitude and belief change with work done on the adoption and diffusion of innovative energy technologies (Kiesling, Günther, Stummer, & Wakolbinger, 2012). Taken together, these two strands of research may deepen our understanding of consumer behaviour within an energy system's context.

Furthermore, this thesis aims to present a clear and *workable* (i.e. formalizable) definition of values and related cognitive constructs. This is relevant since the term "value" often lacks a clear conceptualization (Jones, Shaw, Ross, Witt, & Pinner, 2016) and is generally insufficiently differentiated from related concepts such as attitudes, norms, opinions and/or preferences (Bergman, 1998).

Additionally, our understanding of what causes value change and what the exact effects of value change are on various types of energy consumer behaviour is, as of yet, still lacking (Dietz, Fitzgerald, & Shwom, 2005). The current study addresses this lack of understanding by presenting a potential explanation of how values change and how this process impacts consumer decisions to adopt a CET.

To summarize, this study addresses the knowledge gaps concerning the limited work done on incorporating the sociodynamics of value change (and belief system change in general) within models of energy consumption behaviour (Gotts & Polhill, 2017) and technology adoption (Schröder & Wolf, 2017; Thiriot & Kant, 2008). Stated differently, the current study addresses the underrepresentation of values vis-à-vis other cognitive constructs within models of socio-technical and/or socio-ecological systems (Jones et al., 2016). It also addresses the need for enhancing the psychological realism of social simulations in general (Jager, 2017).

1.1.7 *Practical & Societal Relevance of Thesis*

Radical institutional and technological changes are needed for a successful energy transition. Processes of technological development and radical change within institutional frameworks are contingent upon prior changes in people's value systems (Matutinović, 2007b; Norgaard, 1994). Value change implies that what we do not value in the present might become essential to humans living in the future (Gowdy, 1994). What may seem to be marginal ideologies from a present-day perspective can grow to become the socio-political reality of tomorrow (Gowdy, 1994). Hence, attempts at understanding the process of value change enables one to become more considerate of how the well-being and functioning of societies in the future is affected by decisions made in the present. This line of reasoning clarifies that policies striving for sustainability must take into account the process of value change within human societies.

From a practical perspective, the ECBCS might inspire actors within the energy system to incorporate the notion of value change within their models of strategic forecasting. For example, distribution system operators (DSOs) are actors responsible for managing the physical state and operation of energy distribution networks (i.e. low to medium voltage urban electricity grid and network of gas pipelines). DSOs use computer models that inform them about what parts of the energy infrastructure are at risk of experiencing insufficient transport capacity (e.g. brown- or blackouts) resulting from short-term fluctuations and/or long-term trends in consumer demand. In doing so, DSOs are able to base their investment decisions on the outcomes of such models. DSOs might use models similar to the ECBCS for enhancing their (long-term) scenario planning abilities.

Moreover, policy-makers that use models to gauge the effectiveness of potential policy interventions may find that the ECBCS helps them to enhance their understanding of the long-term consequences of present-day policy-making. All in all, the ECBCS should help strategic decision-makers better anticipate the social subsystem's reaction to interventions within the broader energy system.

1.2 Research Description

Firstly, the problem analysis presented in Section 1.1 is summarized in Section 1.2.1 as the current study's problem statement. Based on this problem statement, the current research objectives and questions are presented. Subsequently, the research scope is delineated. Section 1.2 concludes with a structured overview of this thesis and a description of the intended audience.

1.2.1 Problem Statement

The need for an energy transition has arisen in response to a growing discrepancy between (**A**) what people find important or valuable in life, and (**B**) the performance of – or value delivered by – the physical energy system. Since the physical energy system has not changed much in recent decades, it is clear that changes in people's values are responsible for the currently observed mismatch between **A** and **B**. It is relevant to investigate how – and/or whether – this divergence can be managed as levels of societal discontent rise in proportion to the incongruity between **A** and **B**.

Minimizing the divergence of **A** relative to **B** (and vice versa) calls for a deeper understanding of *how belief system change happens*. Anticipating belief system change may help to forestall the emergence of negative sentiments and consequent destabilization of socio-technical (energy) systems. One way in which belief system change may destabilize the functioning of the Dutch energy system is through altering patterns of consumer energy technology adoption behaviour.

A person's values interact with her knowledge to determine the attitudes he/she holds with respect to clean (i.e. low-carbon) energy technologies. These attitudes, in turn, impact one's intention – and ultimately one's decision – to adopt a clean energy technology. Hence, value and knowledge change induces attitude shifts which subsequently affect consumer intentions to adopt clean energy technologies. The dynamic interplay of values, knowledge, and attitudes is referred to as belief system change.

This thesis focusses on providing a way of thinking about how belief system change happens within an energy-system's context. Additionally, this thesis investigates the usefulness of ABMs as research tools for systematically studying belief system change within socio-technical systems (energy systems in particular).

1.2.2 Research Questions & Objectives

How can the mechanisms embedded within the conceptualization of λ be formalized and studied?

The principal aim of this thesis is to provide a comprehensive answer to the following research question:

How can belief system change and the formation of energy consumer attitudes with regards to clean energy technologies be conceptualized, and can this conceptualization be formalized and studied using an agent-based modelling approach?

The following three sub-questions are formulated in order to answer the central research question. To avoid lengthy questions, the symbol "λ" is introduced, which stands for the complex social phenomenon that is currently studied.

λ = "belief system change and the formation of consumer attitudes towards clean energy technologies."

Research question #1:	*How can the mechanisms that underlie λ be conceptualized?*
Objective #1:	Develop a conceptual (i.e. non-formal) model that integrates the notion of belief system change with the formation of consumer attitudes regarding clean energy technologies.
Research question #2:	*How can the mechanisms embedded within the conceptualization of λ be formalized and studied?*
Objective #2:	Build a proof-of-concept agent-based model that formalizes and simulates the conceptual model mentioned in Objective #1.
Research question #3:	*How useful are agent-based models for building formal representations of λ, and complex social phenomena in general?*
Objective #3:	Provide a critical reflection on the usefulness of agent-based modelling as research tools for systematically studying belief system change within socio-technical systems (energy systems in particular).

1.2.3 Research Scope

This thesis adheres to a *generative science* approach. Traditionally, scientific studies of systems aimed to understand its workings by breaking these down into ever smaller components, and analysing each part in isolation before assembling them back together again (Nikolic, 2009). However, this reductionist approach is not fit for studying complex emergent phenomena such as belief system change. The central principle of the generativist approach is to ask oneself *"How could the decentralized* *local interactions of heterogeneous autonomous agents generate the given regularity?"* (Epstein, 1999, p. 41). In this thesis, the regularity we're interested in is macro-level *intragenerational* belief system change within an energy system's context. Intragenerational belief system change refers to processes of belief change *within* a generation, as opposed to *across* generations (Hassan, Antunes, & Arroyo, 2009). In doing so, there is less focus on demographic dynamics (i.e. birth, death, migratory dynamics) and more on socialization and culturalization processes.

The current conceptual model is grounded in a theoretical framework that is an eclectic synthesis of theories deemed relevant for describing and/or explaining belief system change. For an overview of these theories see Table 1 in Appendix 1.The conceptual model is subsequently formalized using an ABM-approach. The current ABM is referred to as the *Energy Consumer Belief Change Simulator* (henceforth: ECBCS).

The ECBCS builds and extends upon previous simulation studies on the dynamics of psychological constructs (e.g. opinions, attitudes, beliefs) within artificial societies (Becker, Brackbill, & Centola, 2017; Brousmiche, Kant, Sabouret, & Prenot-Guinard, 2016; Flache, 2018; Flache et al., 2017; Friedkin & Johnsen, 1990; Friedkin, Proskurnikov, Tempo, & Parsegov, 2016; Levine, 2003; Mason, Conrey, & Smith, 2007; Meadows & Cliff, 2012; Parsegov, Proskurnikov, Tempo, & Friedkin, 2017; Sobkowicz, 2018). Building and extending upon existing models is prescribed by a modelling strategy called TAPAS or *"Take a Previous Model and Add Something"* (Frenken, 2006). The TAPAS approach ensures modelling efforts are geared towards obtaining a maximum diffusion and accumulation of knowledge with regards to understanding a particular social phenomenon (Edmonds, 2010; Frenken, 2006).

The main reasons for building the ECBCS are to engage in *formalization* and *theory exposition* (see Table 1). The prime objective of experimenting with the ECBCS is therefore to thoroughly explore the consequences of the assumptions embedded in the current conceptualization of belief system change (Edmonds et al., 2019).

Table 1. *Current Modelling Purposes.*

Purpose	What?	Why?
Formalization	Convert the informal assumptions and ideas embedded in the non-formal model of belief system change into a form that is precise, explicit, unambiguous and easily transmitted (Edmonds et al., 2019).	In order to document, share, criticize, and improve upon the current model of belief system change (Edmonds et al., 2019).
Theory Exposition	Investigate how the mechanisms proposed by the non-formal model interact to generate various types of belief change phenomena, and to specify the conditions under which they do so (Edmonds et al., 2019).	In order to refute or support hypotheses about the emergence of belief system change resulting from a particular collection of interacting variables and/or processes (Edmonds et al., 2019).

The human mind cannot keep track of all the interacting variables and processes that underlie the emergence of complex social phenomena such as belief system change (Edmonds et al., 2019). Moreover, ABMs of complex social phenomena generally transcend mathematical tractability. Hence, understanding the behaviour of a model like the ECBCS must be done by running a multitude of simulations. By executing a large number of simulations, it should ultimately become clear *how* various theoretical mechanisms interact and *when* they produce different classes of outcomes (Edmonds et al., 2019). In doing so, researchers can take what they find useful from the ECBCS and apply it within models constructed for other purposes (Edmonds, 2010; Edmonds et al., 2019; Frenken, 2006).

Additionally, this study provides a brief reflection on how the outcomes generated by the ECBCS compare to belief change related phenomena observed in the real world. Note, however, that although the ECBCS may generate processes that correspond to what is observed in the real world, this does *not* mean that the model is able to *explain* belief system change. In other words, conceptualizing belief system change in a particular way does not necessarily render it a valid explanation (Edmonds et al., 2019). For the ECBCS to become a full-fledged explanatory model, its outcomes ought to be thoroughly validated against empirical data (Edmonds et al., 2019) which lies beyond the scope of the current study.

To conclude, this thesis should be considered as a starting point for non-specialists who want to improve their understanding of how values, factual beliefs and attitudes *may* change within an energy system's context. Importantly, the current study places a higher priority on breadth (i.e. inclusivity) than on depth (i.e. accuracy) during the development of the current conceptual model. That is, this study focusses on clarifying what should be included in a model representation of belief system change and what is redundant. Furthermore, much like a scout exploring uncharted terrains, the ECBCS should provide intelligence on whether it makes sense to further invest time and effort towards incorporating belief system change in more elaborate and explanatory models of (energy) consumer behaviour. The author acknowledges the current study's potential lack of theoretical and/or methodological rigor and invites specialists to provide suggestions for improvement in this regard.

1.2.4 Audience

The primary intended audience of this thesis comprises the TU Delft, the Dutch government (i.e. de Rijksoverheid) and Dutch DSOs such as Liander, Stedin and Enexis (Statista, 2016). The secondary audience includes any public or private actor that operates within the boundaries of the Dutch energy system, or any other socio-technical system, and that is interested in gaining a deeper understanding of the sociodynamics of belief systems underlying broad patterns of industrial production and consumption.

1.2.5 *Thesis Overview*

The structure of this thesis is depicted in Figure 3.

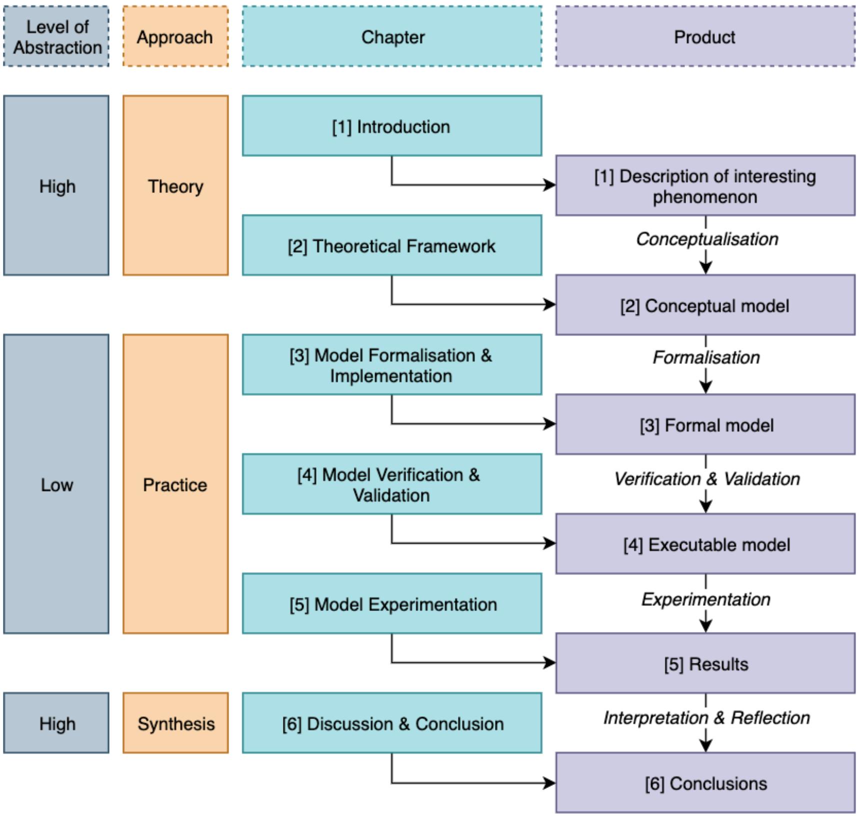


Figure 3. *A Schematic Overview of the Current Research Process.*

1.3 Chapter 1: Recapitulation

Some of the key takeaways presented in Chapter #1 are:

- The Dutch energy system is a complex socio-technical system; transforming it requires a generativist and holistic approach rather than one that is reductionist and mechanical.

- The social system that exists as a part of the broader Dutch energy system is where the deepest, most transformative, opportunities for systemic change reside.

- People hold beliefs about how the world is (factual beliefs), and how the world ought to be (affective beliefs or values). Beliefs are organized into belief systems that act as lenses through which individuals perceive and interpret the world around them. Belief systems consist of two subsystems: a value system and a knowledge system.

- People's belief systems co-evolve with the technological functioning of energy systems; that is, people's beliefs affect, and are affected by, the physical state of the energy system.

- The current need for a radical energy transition has emerged from changes in people's beliefs over the past decades. The changes in beliefs involve the accretion of knowledge (factual beliefs) regarding the detrimental environmental impacts of the energy system, and the increasing importance ascribed to environmental sustainability (affective belief or value).

- The coevolution of belief systems and the physical energy system is a complex process involving technological and institutional lock-ins, strong path-dependencies, and precipitous changes (i.e. punctuations) in, ostensibly stable, equilibrium states.

- Increasing our understanding of belief system change processes within an energy system's context can be done by making it happen before our own eyes through computer simulations.

- Simulating the complex sociodynamics of belief system change requires a generativist modelling tool; ABMs are such tools.

- The current thesis studies whether change in belief systems within an energy system's context can be (credibly) simulated. Moreover, it should point out whether ABMs are an appropriate tool for simulating and studying belief change processes within an energy system's context.

- The ECBCS is *not* built to explain what happens in the real world, but rather to explore the properties of the current conceptualization of belief system change. In doing so, the ECBCS may form the basis for explanation-based ABMs that can be tested to see whether they are able to closely simulate real-word belief change processes.

2 Theoretical Framework

2.1 Chapter Overview

Section 2.2 starts off with a conceptualization of values. Subsequently, the relationship between values and behaviour is described. From this description it becomes clear that values interact with knowledge to form attitudes, which in turn influence behaviour. Hence, conceptualizations of knowledge and attitudes are also provided. Furthermore, studying the relationships between values, knowledge and attitudes calls for a conceptualization of belief systems. Section 2.2 concludes with a conceptualization of culture as it constitutes an important driver of value change.

Section 2.3 uncovers the mechanisms that underpin the change in values, knowledge and attitudes. Table 2 provides an overview of questions that serve to guide the current theoretical literature review.

Table 2. *Overview of Questions Guiding the Literature Review.*

Section		Guiding Questions
2.2	i.	How can values be conceptualized?
	ii.	How are values related to behaviour?
	iii.	How can knowledge be conceptualized?
	iv.	How can attitudes be conceptualized?
	v.	How can belief systems be conceptualized?
	vi.	What are the relations between values, knowledge and attitudes?
	vii.	What functions do values, knowledge and attitudes serve?
2.3	i.	How can change within values be conceptualized?
	ii.	How can change within knowledge be conceptualized?
	iii.	How can change within attitudes be conceptualized?
	iv.	How are values, factual beliefs and attitudes formed?
	v.	How do values, factual beliefs and attitudes influence one another?
	vi.	What explains the heterogeneity in values, factual beliefs and attitudes within a population?
	vii.	What are the main drivers and barriers of change in values, factual beliefs and attitudes?

The author acknowledges that the current conceptualizations are based on a small subset of all the relevant literature available. The reader must therefore keep in mind that the current non-formal model of belief change constitutes one of many ways of thinking about this phenomenon.

Table 1 (Appendix 1) provides an overview of the theories used in the construction of the non-formal model of belief change. Each theory provides a unique contribution to the formulation of a general explanation of how belief change may happen. As should become clear throughout Chapter #2, the nature of belief system change involves a higher degree of complexity than most individual theories would make one believe. This explains the eclecticism that characterizes this study's theoretical framework.

2.2 Key Concepts: Definitions & Relations

2.2.1 Conceptualizing Values

2.2.1.1 Defining Values

Humans are fundamentally motivated to extract meaning from, and make sense of reality in order to resolve ambiguities, reduce complexity, and avoid feelings of confusion and anxiety (Baumeister & Masicampo, 2010; Gelfand & Jackson, 2016). Humans do so by cognitively transmuting the necessities inherent in existence into higher-order guiding principles (i.e. values) that can be communicated effectively (Schwartz, 1994). Values help humans cope with the reality of living in a complex social context (Boyd & Richerson, 2009; Opschoor, 2003; Schwartz, 1994) by providing an authoritative justification for norms that dictate how one is expected to act (Gelfand & Jackson, 2016). In doing so, values guarantee some kind of predictability and stability of the behaviour of individuals and society as a whole (Kostrova, 2018).

Prior attempts at conceptualizing values have produced a large number of definitions. From this pool of definitions, six common features can be extracted that are shared amongst them (Schwartz, 2012), namely:

1. **Values are beliefs inextricably linked to affect.** The activation of values within people automatically infuses their state of being with passion, feelings and emotions. Someone that values egalitarianism, for example, will become aroused and/or angered if it is threatened by people who seek social power, will feel despair if he/she feels powerless to realize it, and will feel content and/or happy when it is fulfilled (Schwartz, 2012).
2. **Values are about desirable end-states of reality that motivate action**. As is mentioned under the first feature, the fulfilment of values *feels* good and/or satisfying. This is why, when primed to do so, people are generally motivated to act in accordance with that which they care about (Stern, 2000).
3. **Values transcend specific situations, actions, and objects.** Values serve as general guiding principles for behaviour and decisions over a wide range of contexts (Anderson, 2018). This is what distinguishes them from norms and attitudes, which apply to more specific situations, actions and/or objects (Schwartz, 2012).
4. **Values serve as standards or criteria.** Values guide the evaluation or selection of behaviours, objects, people, and events (Schwartz, 2012). On the basis of their values, people judge something to be *good* or *bad*, to be *important* or *unimportant*, to be *desirable* or *undesirable*. The impact of one's values on decision-making, however, is not so straightforward as one would expect (see e.g. the *value-action gap* described in Section 2.2.2). Values are found to affect conscious decision-making processes when the actions or judgments one is reflecting upon involves a conflict between different cherished values (Schwartz, 2002).
5. **Values are ordered by relative importance.** People's values are organized in a hierarchical manner (Schwartz, 2012). Hence, values can be compared to one another and ranked in terms of their respective importance within the eyes of an individual or group of individuals. This feature is also one that distinguishes values from norms and/or attitudes.

6. **The relative importance of multiple values guides action.** As noted in feature 4, value conflicts during decision-making tend to make a person become aware of his/her value priorities. That is, the need to make trade-offs among cherished, but competing, values induces conscious reflection on the priorities one ascribes to his/her values. In these situations, values tend to guide and explain someone's behaviour (Schwartz, 2002). Note that people can, and do, pursue competing values but not during a *single act*; that is, people do so through different acts, times and/or settings (Schwartz, 2012).

To sharpen our conceptualization of values it is important to understand the difference between values and related concepts such as: attitudes, preferences, norms, principles, morals, and ethics. Text 1 in Appendix 7 provides a detailed description of how values differ from these related psychological constructs.

2.2.1.2 *Basic Value Theory*

Values represent generalized responses to the *"Universal Requirements of Human Existence & Well-Being"* with which all individuals (and groups of individuals) must deal, and have dealt with over the course of human history (Schwartz, 1994). These universal requirements emerged in response to evolutionary selection pressures; that is, they increased the likelihood of an individual (or groups of individuals) to preserve and replicate oneself (themselves) (Boyd & Richerson, 2009; Wilson, Van Vugt, & O'Gorman, 2008). These universal requirements occur at a micro-, meso- and/or macro-level scale:

1. Micro-level: universal needs of individuals as biological organisms.
2. Meso-level: universal requisites of coordinated social interaction.
3. Macro-level: universal prerequisites for the smooth functioning and survival of large groups.

The Basic Value Theory (BVT) distinguishes ten value types on the basis of these universal requirements, each of which expresses a different goal or motivation (Schwartz, 2012). The goals expressed by each value type are aimed at the fulfilment, or attainment, of particular aspects of reality related to the aforementioned universal requirements. Note that although the nature and structure of the BVT value types may be universal, individuals and groups differ substantially in the relative importance they ascribe to each value type (Schwartz, 2012). Table 2 (Appendix 1) depicts a descriptive overview of the BVT value type and the universal requirements they appeal to.

Each value type is characterized by a set of *exemplary values* (Dietz et al., 2005, p. 348, Table 1); which can be thought of as values that are representative of each value type (Schwartz, 1994, p. 22, Table 1). A value type can be thought of as a hypernym that subsumes values with more specific meanings (see Figure 4). Stated differently, exemplary values (of which there are a near infinite) may be *sampled* from the ten BVT value types (Schwartz, 1994). Note that an exemplary value may belong to more than one BVT value type (see Figure 4). However, an exemplary value cannot belong to value types that are antagonistic.

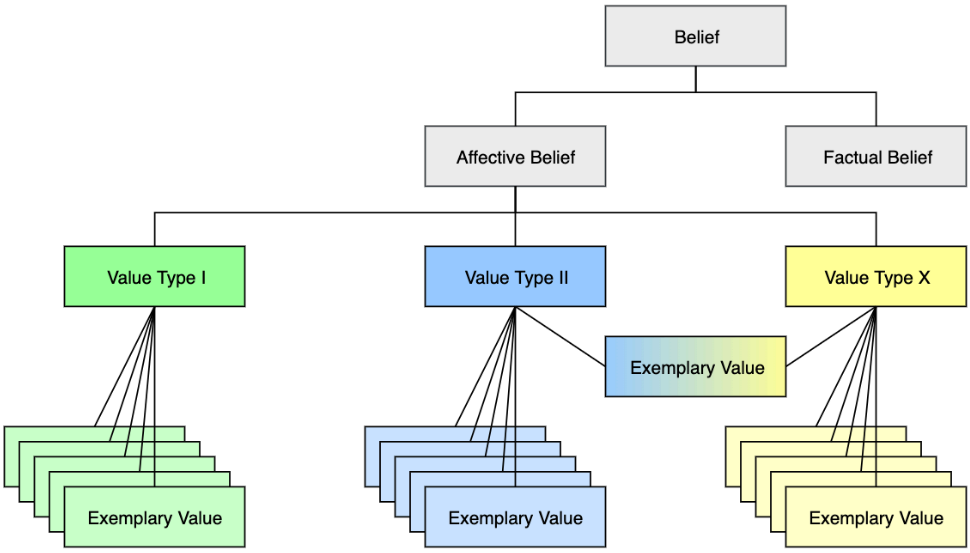


Figure 4. *Visualization of Semantic Relationships Between Value & Belief Constructs.*

The BVT also specifies the structure and dynamism of the relations between each of the value types. Actions in pursuit of any particular value type will have consequences for the other value types (Schwartz, 2012). For instance, pursuing power will conflict with pursuing benevolence; that is, actions aimed at the fulfilment of power are contested by those that are prescribed by benevolence. Values that conflict with one another are referred to as *antagonistic* values. On the other hand, pursuing power does not exclude one from simultaneously pursuing achievement. Values whose prescribed actions harmonize with one another are referred to as *mutualistic* values. The BVT organizes the ten value types in a circular structure (see Figure 3 in Appendix 2); where values placed close to one another are mutualistic, and values placed further away from one another become increasingly antagonistic (Schwartz, 2012). The notions of antagonistic and mutualistic values help to understand how people's value systems can be (logically) structured.

In order to increase our understanding of the way the values types relate to one another, one can place them in a circular structure on a two-dimensional plane. One of the dimension contrasts *self-enhancement* (or personal focus) with *self-transcendence*, and the other contrasts *progression* with *conservation* (Schwartz, 2012). Another way to dimensionalize the circular structure is to tilt the dimensions 45°. This results in a dimension that contrasts *anxiety-based* (prevention of loss) with *anxiety-free* (promotion of gain) values, and another dimension that contrasts *self-* with *other-orientedness* (Schwartz, 2012). Figure 2 (see Appendix 2) provides a visualization.

2.2.2 *Values & Energy Consumer Behaviour*

Traditionally, consumer behaviour is explained through the microeconomic lens of the 'rational actor' model. The consumer was presumed to behave as a fully rational utility-maximizing *homo economicus* with preferences that are ordered, known, invariant, and logically consistent (Wilson & Dowlatabadi, 2007). According to this model people act or make decisions by weighing alternatives in comparison with their preferences (Dietz et al., 2005). The decision-maker eventually chooses the option that performs best in matching with her preferences. Note that 'decision making' is treated here as a synonym to 'behaviour' or 'acting'.

However, preferences often conflict during decision-making. In these situations, values may inform a decision-maker on the prioritization of her preferences (Dietz et al., 2005). Importantly, the influence of values on decision-making is contingent upon the quality of the decision-making context (Dietz et al., 2005). Specifically, someone that has to make a decision within a context that is novel and unfamiliar will likely reflect on her values to come to a resolution. Conversely, decisions that have become routine preclude the potential influence of values on decision-making behaviour. The adoption of a CET is considered a non-routine decision. In other words, adopting a CET requires a conscious deliberation on part of the decision-maker. Hence, values are likely to play an important role in this regard.

However, even during deliberate decision-making, people do not always act in perfect accordance with their values and intentions (Frederiks, Stenner, & Hobman, 2015). Recent findings within the fields of psychology and behavioural economics show that the rationality behind energy-related consumer behaviour is often distorted by various cognitive biases and heuristics (Frederiks et al., 2015). These cognitive biases and heuristics are able to explain much of the observed inconsistencies between what humans *say* and what they *do* (Frederiks et al., 2015). Examples of such 'walk-the-talk' inconsistencies are the knowledge-action gap (Courtenay-Hall & Rogers, 2002), the value-action gap (Flynn, Bellaby, & Ricci, 2009; Kennedy, Beckley, McFarlane, & Nadeau, 2009; Leiserowitz, Kates, & Parris, 2006), and/or the attitude-action gap (Claudy, Peterson, & O'Driscoll, 2013).

Not only do human limitations in rational information processing form an obstacle to directly translating values and attitudes into action, there are at least three other types of barriers. First, values are often incommensurate which means they can conflict with one another during decision-making (Leiserowitz et al., 2006). This fact is exemplified by the so-called *energy trilemma* (Bale, Varga, & Foxon, 2015); which refers to the difficulty of balancing the economic, social and environmental performance of energy technologies. As with the energy trilemma, it is generally the case that value trade-offs must be made during decision-making (van de Poel & Royakkers, 2011). Making these trade-offs implies that the strength (importance) of a particular value undermines the priority ascribed to another (van de Poel & Royakkers, 2011). An example is that although environmental sustainability is perceived to be increasingly important, a higher value ascribed to economic growth on the macro-scale, and/or personal wealth on the micro-scale, generally trumps the influence of the former during energy-related decision-making (Leiserowitz et al., 2006).

Another barrier to the adoption of CETs can be found in an individual's perceived lack of efficacy of translating her values into action. Such perceptions can occur when a person lacks the time, money, access, knowledge and/or power to fully incorporate her values into decision-making processes (Leiserowitz et al., 2006). Additionally, a person's values might not always harmonize with the nature of one's personal habits and behavioural routines. Since breaking away from routines and habits is difficult, a value-action gap is likely to manifest (Leiserowitz et al., 2006; Sustainable Development Commission, 2006) and is often perpetuated by irrational mental distortions aimed at reducing cognitive dissonance (Harmon-Jones, Amodio, & Harmon-Jones, 2009).

A third type of barrier is structural. Examples are perverse incentive structures, institutional barriers, infrastructural restraints, socio-cultural expectations, and norms (Leiserowitz et al., 2006; Sustainable Development Commission, 2006). Consumer adoption of CETs may deal with a combination of different types of barriers across spatial and temporal scales, social segments in society, and/or at different levels of decision-making (individual versus legislature) (Leiserowitz et al., 2006).

A model that explains how values are related to behaviour, whilst potentially accounting for all of the aforementioned mediator and moderator variables, is the Theory of Planned Behaviour (TPB) (Ajzen, 1991; Armitage & Conner, 2001). According to the TPB, values and knowledge shape attitudes, which, in combination with subjective norms and perceived behavioural control, determine one's intentions to act in a certain way (see Figure 5). Subjective norms refer to the social pressure one experiences to perform (or to not perform) certain types of behaviour (Armitage & Conner, 2001); e.g. one may want to adopt a CET because her peers will approve of that. Perceived behavioural control refers to the constraints on particular behaviour that an individual may perceive (Armitage & Conner, 2001); e.g. one may experience a lack of financial means needed to adopt a CET. Figure 5 provides a visualization that is based on the TPB model (Armitage & Conner, 2001, p. 472, Fig. 1); note that the variable marked with an asterisk is added by the author for the sake of completeness. Observe also that the highlighted variables delimit the scope of the current study.

Thus, values are only distally related to consumer behaviour (Hitlin & Piliavin, 2004) (see Figure 5). Nonetheless, values *do* affect behaviour, albeit indirectly and/or under specific circumstances (Hansen, 2008; Hitlin & Piliavin, 2004; Homer & Kahle, 1988; Pepper, Jackson, & Uzzell, 2009; Stern, 2000; Verplanken & Holland, 2002). Hence, on the level of individual decision-making, values might not be such a reliable predictor of consumer CET adoption behaviour. However, on a (spatial and temporal) macro-scale they are well able to explain trends in broad patterns of energy consumer behaviour (Antonides & van Raaij, 1998; Çileli, 2000; Dietz et al., 2005; Hassan et al., 2009; Hitlin & Piliavin, 2004; Inglehart & Baker, 2000; Leiserowitz et al., 2006; Matutinović, 2007b; Voicu & Telegdy, 2016; Welzel, Inglehart, & Kligemann, 2003).

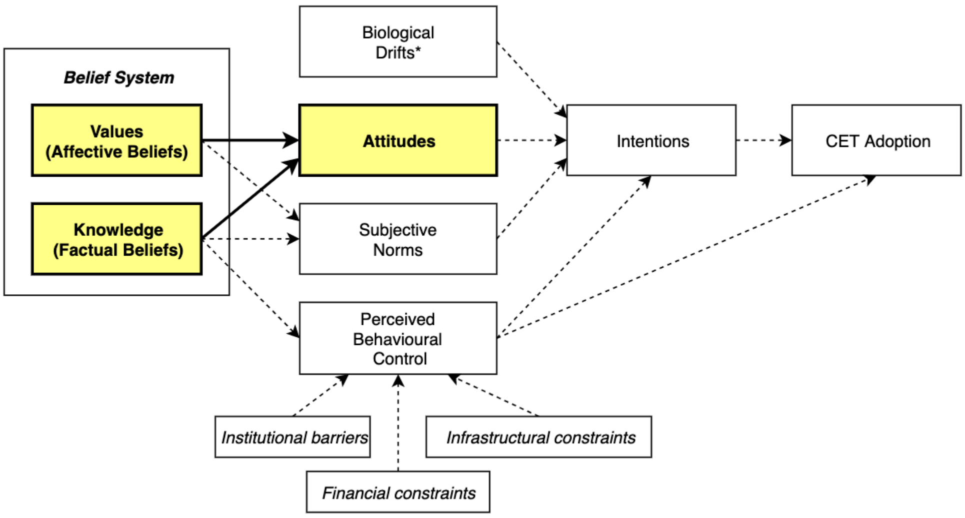


Figure 5. *Conceptual Model of How Values Affect CET Adoption Behaviour.*

Note: the scope of this study is limited to studying how changes in values and knowledge lead to changes in attitudes. The non-highlighted variables and processes included in Figure 5 are included for illustrative (contextual) purposes only.

The following sections provide a conceptualization of knowledge, attitudes and belief systems. These conceptualizations are needed to obtain an accurate understanding of how values underpin the formation of consumer attitudes towards the adoption of CETs.

2.2.3 *Conceptualizing Knowledge*

The current study conceptualizes knowledge as a system of *explicitly held factual beliefs* about how things in the world are related in particular ways. Explicitly held beliefs are those which a person is aware of holding (Burrus & Carney, 2015). Specifically, within the ECBCS, an agent's knowledge relates to its awareness of what the consequences are of adopting a CET for the physical and psychological well-being of oneself and others. Hence, an agent is 'knowledgeable' when it is accurately aware of how the use of a CET affects reality.

Note that the term 'factual belief' carries with it the connotation of disputability; which indicates that the holder of a particular set of factual beliefs is aware that others may think differently (Abelson, 1979). This implies that facts about the world are tied to subjective probabilities that define their perceived veracity (Chai, 2009). Conceiving of knowledge in this way presumes that the notion of 'truth' is something that is fluid and subjective.

2.2.4 *Conceptualizing Attitudes*

2.2.4.1 *Defining Attitudes*

An attitude is a summary evaluation of an object, or entity, expressing some degree of favour or disfavour (Fazio, 2007; Nordlund, 2009; Urbig & Malitz, 2005). Attitudes are formed on the basis of a network of factual and affective beliefs that become, to differing degrees, activated when an individual is prompted to evaluate a particular object or entity (Bergman, 1998; Bodur, Brinberg, & Coupey, 2000; Thorngate & Tavakoli, 2009; Urbig & Malitz, 2005); see Figure 6. Note that attitudes themselves are not beliefs, but can rather be thought of as the *evaluative component* of a set of beliefs (Burrus & Carney, 2015).

The current conceptualization of attitudes may lead to four situations wherein a pair of individuals hold dissimilar attitudes towards identical objects (Bergman, 1998):

1. Similar cognitive construction, similar evaluation
2. Similar cognitive construction, dissimilar evaluation
3. Dissimilar cognitive construction, similar evaluation
4. Dissimilar cognitive construction, dissimilar evaluation

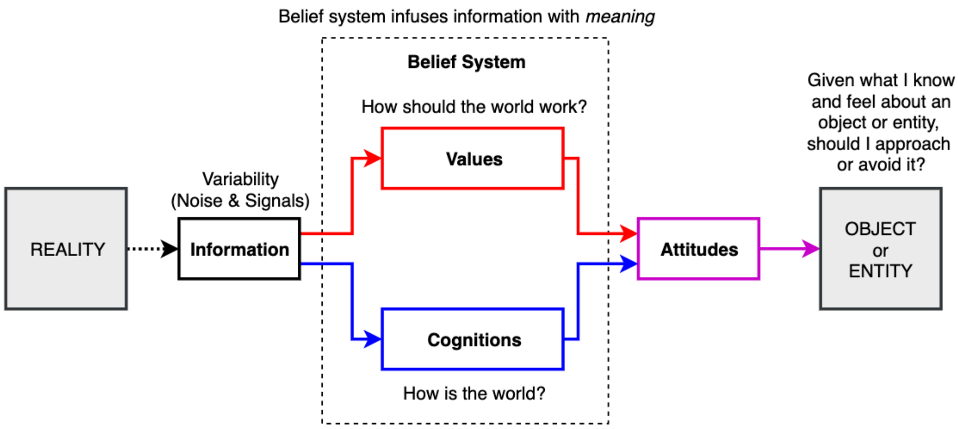


Figure 6. *Conceptual Scheme of How Attitudes are Formed.*

The activation of certain beliefs during an evaluative instance is proportional to the accessibility, or salience, of those beliefs during that moment (Armitage & Conner, 2001; Bergman, 1998). Furthermore, the quantity and qualitative properties (e.g. evaluative consistency) of beliefs that underpin the formation of an attitude ultimately determine the attitude's strength and valence (Tesser & Shaffer, 1990). More specifically, a high (low) evaluative consistency between beliefs leads to a more extreme (moderate) attitude (Tesser & Shaffer, 1990). To illustrate this, suppose someone is asked to express her attitude towards the decision by the Dutch government to close all of the nation's coal-fired power plants (Rijksoverheid, 2017). Deliberating on this issue will likely bring into conflict the values related to environmental sustainability and economic security. Dealing with these conflicting values is reflected back into a more complex cognitive structure which generates a more moderate attitude towards the issue (Tesser & Shaffer, 1990).

Attitudes form an intermediary step between (a) one's value system and factual understanding of reality and (b) one's behaviour. In general, the more favourable (unfavourable) the attitude towards a certain action, the stronger the individual's intention to perform (not perform) it (Armitage & Conner, 2001). To illustrate, suppose an individual cherishes biospheric values but is not aware of anthropogenic climate change. She will continue to use carbon-rich technologies (e.g. a diesel car) despite valuing the environment. This discrepancy can be explained by the fact that this person perceives reality in a way that neglects the link between carbon emissions and environmental damage. As soon as this person finds out about this link, it is likely, though not guaranteed, that she intends to stop driving that diesel car.

Logical discrepancies between what a person values and knows, and how she subsequently acts can often be explained as a way of dealing with cognitive dissonance. For example, someone that values environmental sustainability but continues to drive a polluting diesel car may tell herself something along the lines of "*Considering the scope and scale of global climate change problems, my individual actions won't make the slightest difference*" or "*I don't have the resources to act in accordance with that which I value*". Endorsing such factual beliefs serves to reduce the tension brought about by cognitive dissonance.

2.2.4.2 Attitude Function Domains

Attitudes broadly serve two functions: an *instrumental* and a *symbolic* function. The latter can be split up into a *social-adjustive*, and a *value-expressive* function (see Table

3) (Mai & Olson, 2000; Tesser & Shaffer, 1990). The instrumental function states that attitudes serve to interpret and categorize objects or events in order to decide whether to avoid or approach these stimuli (Tesser & Shaffer, 1990). Instrumental (or utilitarian) beliefs do not link the stimulus object to other mental structures such as values, perceived norms and/or other attitudes (Mai & Olson, 2000). The social-adjustive function states that attitudes can serve as mediators of social relations; i.e. people connect through the expression of similar attitudes (Tesser & Shaffer, 1990). The value-expressive function states that attitudes can also serve as vehicles for expressing internalized values that are central to the self-concept; that is, people can use attitudes to base and express their identity on (Tesser & Shaffer, 1990). Symbolic beliefs render a stimulus object a means to an end (e.g. self-expression, social-bonding), rather than an end in and of itself (Mai & Olson, 2000). Generally speaking, the symbolic function of attitudes helps people manage their intrapsychic well-being, whilst the instrumental function of attitudes helps one maintain a healthy physical state (see Table 3).

Table 3. *Overview of Attitude Function Domains and Their Properties.*

Attitude Function Domain	Function Type	Social Orientation	Dominant Purpose
Utilitarian[a]	Instrumental	Self-oriented	Ensure physical well-being
Value-expressive[b]	Symbolic	Self-oriented	Ensure psychological well-being
Social-adjustive[c]	Symbolic	Other-oriented	Ensure psychological well-being

a = abbreviation is UTIL.
b = abbreviation is VEX.
c = abbreviation is SADJ.

2.2.4.3 *Attitudes Towards Clean Energy Technologies*

An energy consumer's attitude towards a CET is a function of her belief that the adoption of that CET leads to particular consequences that are deemed (dis)favourable. In other words, given what someone knows about a particular CET, she forms, and/or updates, her assessments of how the use of that CET is likely to affect her well-being. If a person feels that the personal, or public, use of a CET should increase (decrease) her well-being, then her attitude will be positive (negative).

A CET may be decomposed into a collection of *tech-attributes*; each of which can be evaluated by an observer. The selection of tech-attributes included in the ECBCS model is based on the features of energy technologies (and systems) outlined in Demski et al. (2015, p. 64, table 1), Künneke et al. (2015, p. 120) and in Moglia et al. (2017, p. 175, table 2). Table 4 (Appendix 1) provides an overview of the tech-attributes considered to be most relevant for describing the performance of CETs.

The performance that a CET displays on each of these tech-attributes is expressed relative to the performance of other 'competing' energy technologies. Technologies compete when they serve a similar set of consumer needs. Presumably, when a CET outperforms its competitor(s), then people are more likely to adopt it. Whether the relative performance of a CET on a particular attribute is 'better' (or 'worse') depends on the subjective evaluation of an observer. More specifically, a CET may exhibit a 'higher' or 'lower' performance on some attribute, which may then be judged as 'better' or 'worse' depending on an observer's value system. The aggregation of attribute performance assessments is presumed to determine an energy consumer's overall attitude with regards to a particular CET (see Figure 7).

Figure 7 shows how energy consumers form their attitudes towards CETs. Consumers are to varying degrees aware of the relative performance levels regarding a CET's attributes. Consumers evaluate attribute performance levels on the basis of one, or a combination of, attitudinal function(s). Importantly, an attribute holds three weights – i.e. $\{\omega_{Utilitarian}, \omega_{Value\text{-}Expressive}, \omega_{Social\text{-}Adjustive}\}$ – that signify the extent to which its performance is assessed on the basis of the three attitude functions described in Table 3.

Some attributes are more likely to appeal to the utilitarian function, whilst others may be more conducive to satisfying the symbolic functions. For instance, a consumer may evaluate the purchasing cost of a CET on a utilitarian basis, which means that the higher the cost, the lower (more negative) the evaluation. This is because spending money reduces a consumer's overall ability to satisfy its needs. On the other hand, a consumer may evaluate purchasing cost on a social-adjustive basis. In this case, a higher purchasing cost can lead to a higher (more positive) attribute performance assessment. This is because a consumer may feel that it is important to exhibit (material) wealth, or affluence, in order to ensure or increase its social status. Note that for the social-adjustive function to become activated, a CET must be visible and/or differentiated. This is because visible and differentiated products help individuals accentuate their social identity (Brick, Sherman, & Kim, 2017; Grewal, Mehta, & Kardes, 2000; Stets & Burke, 2000).

Furthermore, a consumer may believe that an important purpose in life is to ensure the well-being of all living things. It is therefore motivated to protect nature and/or reduce its impact on the environment as much as possible. Such an agent will have internalized universalistic values, which leads her to express these values through a positive evaluation of a CET's high environmental performance. This example illustrates the formation of an attitude on the basis of the value-expressive function.

Table 5 in Appendix 1 shows how each tech-attribute addresses one or more attitude functions. The theoretical links between the BVT value types and Attitude Function Domains are based on the description of BVT value types (see Table 2, Appendix 1) and judgment of the author.

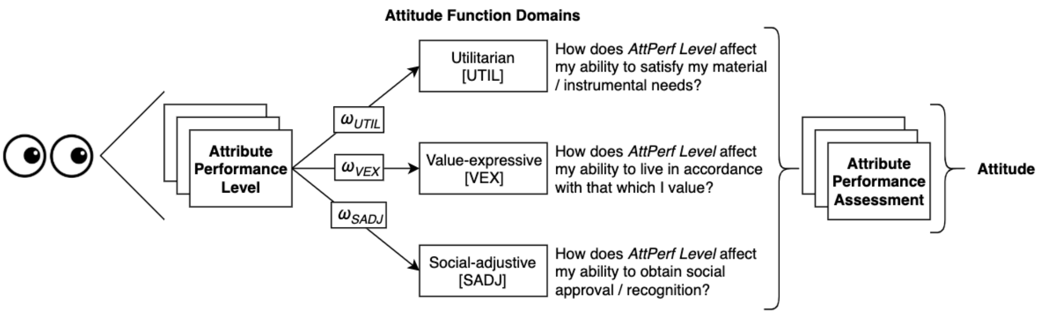


Figure 7. *Conceptualization of CET Attitude Formation.*

2.2.5 Conceptualizing Belief Systems

Belief system theory is a social psychological theory of cognitive organization that attempts to understand and explain stability and change in people's beliefs (Quackenbush, 1989). Belief system theory postulates that various types of beliefs are logically and functionally interrelated, forming a mental structure that is referred to as a *belief system* (Abelson, 1979; Abelson & Carroll, 1965; Barton & Parsons, 1977; Grube et al., 1994; Homer-Dixon et al., 2013; Quackenbush, 1989; Rokeach, 1985, 1994; Tesser & Shaffer, 1990).

Belief system theory helps to make links between values (affective beliefs), knowledge (factual beliefs) and attitudes. Specifically, it enables one to envisage and model beliefs and attitudes as nodes, tied up with one another within a network topology (Homer-Dixon et al., 2013). The connections between the nodes (i.e. the *edges*) can have characteristics such as directionality, strength, valence and memory. Moreover, the relative distance of nodes within the network structure may represent the qualitative (semantic) similarity, or relatedness, of beliefs. For a more detailed description of belief systems, the interested reader is referred to Text 3 in Appendix 7.

Importantly, belief systems form a layer within a nested multi-level structure of emergence (Holling, 2001; Mittal, Diallo, Tolk, & Rouse, 2018). Each layer within the emergence hierarchy is qualitatively different from the others; that is, higher layers constitute something more than the sum of their lower-layer parts. Moreover, higher layers tend to impose constraints on their lower layers, whereas lower layers tend to destabilize higher-order levels (Holling, 2001). Figure 8 helps one gain a deeper understanding of the mechanisms underlying belief system change.

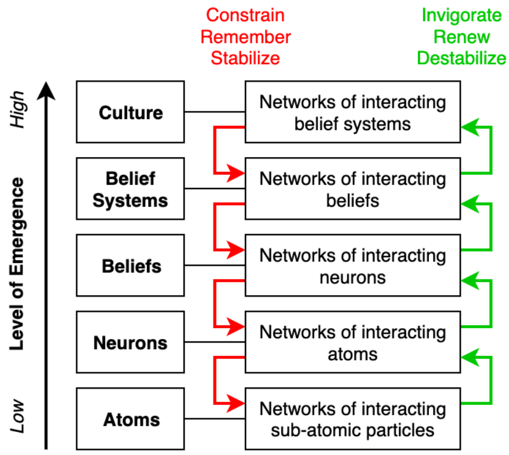


Figure 8. *Belief Systems Forming a Layer Within a Nested Structure of Emergence.*

As can be seen in Figure 8, a collective of 'interacting belief systems' – i.e. people interacting with each other and thereby influencing each other's beliefs – gives rise to the emergence of culture. Culture can be thought of as a macro-level belief system; that is, the belief system of a society rather than that of an individual. Interestingly, culture feeds back on the content and configuration of individual belief systems that constitute it (Holling, 2001). Hence, understanding belief change requires a conceptualization of culture.

2.2.6 *Conceptualizing Culture*

Spencer-Oatey (2012) identifies a set of key features that are shared amongst the many conceptualizations of culture that exist within the literature. A subset of these features is chosen to construct the definition of culture that will be used throughout this thesis. The following paragraphs present and describe these features.

1. **Culture is associated with social groups.**

Culture is inherently something that is *shared* amongst individual members of a social group (Avruch, 1998). People always belong to a number of social groups, each holding their own (sub)culture. Being members of a combination of social groups implies that people are, at any given time, influenced by a variety of *multi-cultural* forces.

2. **Culture is both socially *and* psychologically distributed within a population.**

Since social groups hold different cultures and since people belong to different social groups, culture is *socially distributed* within a given population. Moreover, culture is not uniformly distributed within a given social group. There exist individual differences in the degree to which people adopt and engage in particular beliefs and behaviours that, by consensus, constitute a social group's culture (Brinkman & Brinkman, 1997; Matsumoto & Juang, 2016). Moreover, the same individual may, over time, change his/her conformity with regards to a social group's culture (Avruch, 1998). The non-uniform intragroup distribution of culture means that it is also *psychologically distributed* within a population.

3. **Culture is learned through a process of culturalization.**

Culture is, essentially, a derivative of individual experience. It is something learned and/or created by individuals, or passed on to them by social peers and/or ancestors (Avruch, 1998). This process of social learning is referred to as *socialization*. The effect of socialization is particularly strong during the earlier stages of life (Alanen, 1988; Haidt & Bjorklund, 2007; Healy & Malhotra, 2013), which implies that family and childhood education are important sources of cultural transmission. The current thesis refers to the socialization (i.e. social learning) linked to cultural transmission as *culturalization* (Davis, Hennes, & Raymond, 2018). Although there exist variation in culturalization across families and schools, it is the similarities amongst them that form the basis of a nation's, or social group's cultural profile (Lustig & Koester, 2010).

4. **Culture is subject to gradual change.**

Although some cultures tend to be more conservative than others, change is a constant feature of all of them. The more modern, industrialized, and complex a society is, the more rapid the process of cultural change (Ferraro, 2002). The reason for this is that the intensity of technological development is a principal driver of cultural change (Ferraro, 2002)

Cultural change can occur endo- or exogenously. Endogenous cultural change happens through collective belief change within a culture's boundaries (Ferraro, 2002); a process referred to as *cultural drift* (Centola, Gonzalez-Avella, Eguiluz, & Miguel, 2007). Exogenous change occurs through a process of *cultural diffusion*. Cultural diffusion involves the spreading of cultural items and/or standards from one culture to another (Ferraro, 2002). The current study focusses on cultural drift rather than diffusion.

2.3 Change Processes

The current thesis focusses on conceptualizing the change in factual and affective beliefs. Factual and affective beliefs are hypothesized to underpin the formation of attitudes (Bodur et al., 2000; Tesser & Shaffer, 1990; Trafimow & Sheeran, 1998). Note that beliefs will always have some degree of affect and some degree of cognition. Nonetheless, it seems reasonable to presume that some beliefs are 'more affective' whereas others are 'more cognitive' (Trafimow & Sheeran, 1998), which justifies the dichotomization.

The following sections describe the process of change within affective and factual beliefs as well as the most important drivers of such change. A distinction is made between micro-, meso- and macro-level drivers. It is argued that the micro-meso-macro distinction lends itself well for the analysis of evolving systems (Dignum, Dignum, & Jonker, 2008; Dopfer, Foster, & Potts, 2004; Geels, 2002; Liljenström & Svedin, 2005). Since beliefs are presumed to be organized into systems that adapt and evolve, the application of the micro-meso-macro analytical structure seems justified. This also implies that the current thesis deals with modelling *multi-level* intragenerational belief change.

What distinguishes levels is the *scope* of change processes. Micro-level change concerns *one* agent, meso-level change concern a *subset*, or community, of agents, and macro-level change affects an *entire set* or *population* of agents (see Figure 9).

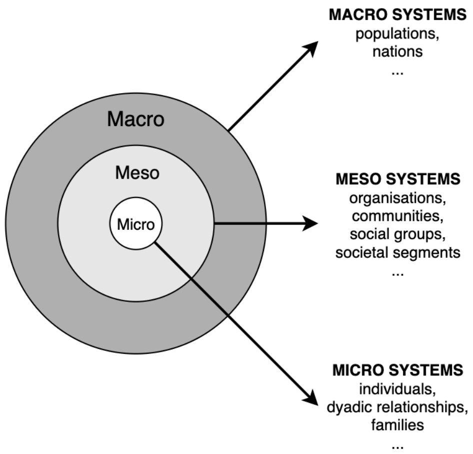


Figure 9. *Visualization of Different Levels of Analysis.*

2.3.1 Value Change

2.3.1.1 Dewey's Value Theory

The BVT framework helps to model the content and structure of people's value systems. Modelling the *change* in people's value systems requires an additional theoretical perspective. A perspective that helps to model value change processes is provided by the pragmatic moral philosopher John Dewey (1859 – 1952) (Swierstra, 2013; Swierstra, Stemerding, & Boenink, 2009; van de Poel, 2016).

Each BVT value type encapsulates a set of exemplary values. From the perspective of Dewey's Value Theory (see e.g. Anderson, 2018), these exemplary values may be thought of as generalized conceptualizations of well-tested responses to (morally) problematic situations that people have been dealing with over the course of human history.

A morally troubling situation is understood as any situation that incites hesitation and/or doubt within an individual (or group of individuals) about what is the 'right' thing to do or 'right' way to act (Anderson, 2018). The troubling features of a situation may be defined in a variety ways, such as the presence of confusion, conflict, unmet needs, unfulfilled desires, danger, obstacles *et cetera* (Anderson, 2018). Values help an individual formulate a decision on how to behave when exposed to such feelings of doubt and/or unease (Anderson, 2018). This implies that values are *valuable* because their guidance leads to certain behaviours that generally result in *positive* consequences to the value-holding individual or group (Anderson, 2018). Note that positive consequences imply a (temporal or final) resolution of the troubling features present within a given situation to which an individual or group is exposed.

Dewey notes that we test our values by acting upon them and consequently deciding whether the results of our actions are satisfactory. A value is considered to be successful when it promotes actions that are able to resolve our problems with acceptable side-effects, when it enables the formulation of satisfactory responses to novel problems, and/or when acting in accordance with alternative values does not yield more satisfactory results (Anderson, 2018).

From this perspective, values undergo an evolutionary process of variation, selection and retention. The problems one must deal with in order to meet the universal requirements of human existence can be addressed by an infinitely variable set of courses of action, or *action pathways*. A value specifies a subset of action pathways deemed to be most suitable for addressing the problem at hand. That is, a value specifies that *"...if something were done, then certain consequences would follow, which would be valued"* (Anderson, 2018). Different values specify different subsets of 'suitable' action pathways.

For instance, dealing with the environmental pollution of one's energy consumption can be done in a myriad of ways, such as: (A) buying a stylish electric vehicle, or (B) donating funds to forest-regeneration initiatives. Values related to social status and wealth (which relate to the 'Power' value type) would promote A, whereas values related to the natural world (which relate to the 'Universalism' value type) would promote B. Over time, different people implement different value-prescribed action pathways to deal with similar problems; this represents the process of variation. Values that guide behaviour down action pathways that result in satisfactory consequences for a majority of people following them are ultimately selected and retained (Anderson, 2018).

2.3.1.2 Combining Basic Value Theory & Dewey's Value Theory

Dewey's pragmatic take on values (see e.g. Anderson, 2018), in combination with the BVT of Schwartz (2012), provides a conceptualization of values that is both comprehensive and practical. Specifically, the BVT provides the ability to equip agents with a structured set of (universal) value types and Dewey's philosophical account provides a way of thinking about how values change.

It must be noted that, from a philosophical standpoint, combining the BVT with Dewey's Value Theory is conceptually disputable. For a brief discussion of why this is the case, see Text 2 in Appendix 7.

Despite their inconsistencies, Dewey's Value Theory and the BVT proclaim that values are formed, predominantly, on the basis of social interaction. Dewey, for instance, claims that "...*over one's life, communication with other individuals shapes and reshapes the emphasis we place on values*" (Dietz et al., 2005, p. 363). In a similar sense, Schwartz (1994, p. 21) states that values are "...*acquired through socialization to dominant group values*". Furthermore, both theories subscribe to the notion that values help humans cope with the complexity of reality during decision-making.

To conclude, the current study acknowledges the existence of conceptual discrepancies between the BVT and Dewey's Value Theory. However, it chooses to combine them based on the conviction that, on a practical level, their amalgamation provides an interesting way of thinking about how values may change.

2.3.1.3 *Conceptualizing the Value Change Process*

Figure 10 shows how the BVT and Dewey's Value Theory can be combined to conceptualize value change. The following bullet-points provide a description of each link depicted in Figure 10:

1) Link #1 shows how individual values are shaped by processes of socialization and culturalization.
2) Link #2 depicts how perceived instability within one's environment increase the exposure of an individual or a group to morally troubling situations. Link #2 is based on the presumption that a higher degree of instability within an environment (or system) leads to an increase in the occurrence of unforeseen events; that is, a decrease in the ability to forecast or make sense of things. Hence, higher instability leads to more frequent occurrences of situations wherein people are impelled to consciously reflect upon their value systems. This presumption is illustrated by the notion of *technomoral change*, which explains how technological developments may destabilize the status quo and prompt people to begin to question the things that up until then seemed self-evident (Swierstra, 2013).
3) Link #3 shows how actions lead to the formation of values (as explicated by Dewey's Value Theory).
4) Link #4 represents how values prescribe particular actions.
5) Link #5 shows how the exemplary values that belong to a particular BVT value type guide behaviour towards addressing the universal requirements of human well-being and existence.
6) Link #6 describes how the BVT value types are underpinned by these universal requirements. If these requirements were to change in some way (either conceptually or objectively), so would the BVT value types.

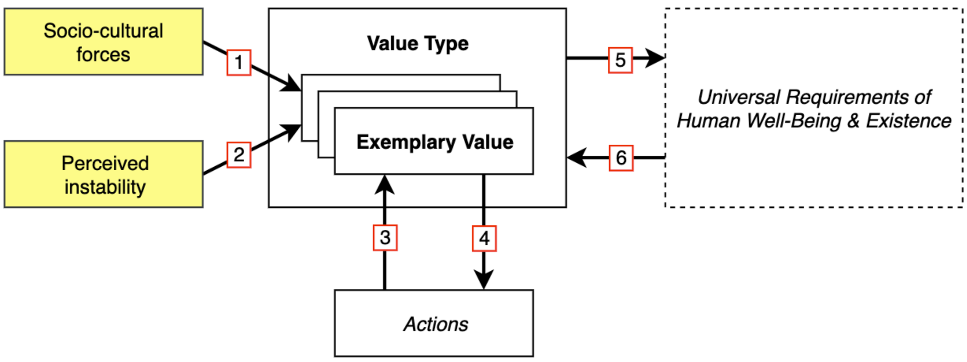


Figure 10. *Conceptualization of the Value Change Process.*

It is important to note that the ECBCS does *not* include a representation of how exemplary values are reciprocally related to behaviour as this lies beyond the scope of the current study. However, the ECBCS does include a representation of how socio-cultural forces and perceived instability affect people's values, which is why these variables are highlighted in Figure 10.

Lastly, the status of a value type (i.e. whether it is cherished or detested) is believed to be a function of:

(A) The size of the set of exemplary values [$\boldsymbol{S}$] that is related to a particular value type [$_{VT}$].
(B) The importance ascribed to each exemplary value that resides within $\boldsymbol{S_{VT}}$.

If an individual or group develops a different conceptualization of how reality ought to be, then $\boldsymbol{S_{VT}}$ changes. For instance, the advent of digital technologies broadened the conceptualization of privacy (Koops, Newell, Timan, Chokrevski, & Gali, 2017). In doing so, the BVT value types that underlie privacy (i.e. Security, Self-direction) gained in conceptual richness. The importance assigned to each value within a particular $\boldsymbol{S_{VT}}$ ultimately determines the status of that value type. The ECBCS does not explicitly model this process, though it is implicit in the way value types are allowed to vary in importance.

2.3.2 *Knowledge Change*

The following section describes **links 8 and 10** in the non-formal model of belief system change (see Figure 5, Appendix 2).

Individuals are assumed to obtain and update their factual understanding of the world by:

1) Acting upon reality and directly experiencing the consequences of those actions (e.g. experiential learning).
2) Observing other people act upon reality and vicariously experiencing the consequences of their actions (e.g. social learning).
3) Conversing with others and sharing experiences.
4) Educating oneself (i.e. reading, studying, watching documentaries *et cetera*).

The ECBCS includes a representation of only [3] and [4].

2.3.3 *Drivers of Belief System Change*

The information that impacts a person's beliefs can come from a large variety of sources, some more impactful than others. A non-exhaustive list of information sources are direct personal experiences, social interaction, media exposure and culturalization. An overview of information sources included in the ECBCS model is depicted in Table 4.

Table 4. *Overview of Information Sources Included in the ECBCS Model.*

	Direct	Indirect		
Category	Personal experience [micro]	Social interaction [meso]	Media exposure [meso]	Culturalization [meso/macro]
Instances	Introspection Disruption of routines	Peers Non-peers	Mass media Niche media Expert media	Social group Population

Factual and affective beliefs are presumed to respond differently to various sources of information (see e.g. Chen & Chaiken, 1999; Evans, 2008; Petty & Cacioppo, 1986; Zajonc, 1980). It is assumed that individuals process incoming information through either a *cold* or *hot* cognitive route (Wolf, Schröder, Neumann, & de Haan, 2015). Cold information is highly factual and carries (very) weak emotional content. Hot information, in contrast, is characterized by relatively strong emotional content (Hatfield, Cacioppo, & Rapson, 1993). Hot information is about what is important to some individual or group and therefore carries a normative tone. Cold information is descriptive; it is about the causal mechanisms that aim to explain real-world phenomena. Information processed via the cold route predominantly affects an individual's factual beliefs, whilst information travelling through the hot route influences its affective beliefs (Wolf et al., 2015).

2.3.4 *Micro-Level Drivers of Belief System Change*

Micro-level drivers of belief change affect *one* individual at a time. The drivers described in the following sections appeal to the immediate experiential worlds of individuals. In other words, micro-level drivers relate to the direct, first-hand experiences of individuals.

2.3.4.1 *Introspection*

> The following section describes **link 6** in the non-formal model of belief system change (see Figure 5, Appendix 2).

A distinction can be made between *internal* and *external* micro-level drivers. An example of an internal micro-level driver is the need for an individual to seek cognitive consistency among its beliefs (Nordlund, 2009). This need for consistency is exemplified by the feelings of discomfort that arise when one experiences cognitive dissonance (Harmon-Jones & Harmon-Jones, 2007). There are generally three ways an individual is able to eliminate dissonance, namely: by reducing the importance ascribed to dissonant beliefs, by adding more consonant beliefs that outweigh the dissonant beliefs, or to alter the dissonant beliefs as to resolve the inconsistency (Nordlund, 2009).

The notions of antagonistic and mutualistic values help to determine the degree of consistency of a belief system. Specifically, antagonistic values can be regarded as *dissonant affective beliefs*, and mutualistic values as *consonant affective beliefs*. Thus, an individual may not consistently cherish antagonistic values simultaneously, since this is presumed to generate cognitive dissonance. When primed to do so, individuals will engage in restructuring their belief systems as to ensure or increase cognitive consistency.

2.3.4.2 *Technological Disruption of Routines*

> The following section describes **link 2** in the non-formal model of belief system change (see Figure 5, Appendix 2).

An external micro-level driver is the technology-mediated disruption of an individual's behavioural routines. New technologies can directly alter someone's perception of reality and/or of the self. Technology can expose information previously hidden from sight, and bring within reach actions that were previously beyond one's capabilities (Waelbers & Swierstra, 2014). In doing so, technological innovations can expose and draw attention towards the potential inconsistencies of values and norms embedded in one's routines (Swierstra, 2015). This may prompt a process of critical or reflective introspection which in turn leads to a change in beliefs.

2.3.4.3 Micro-Level Heterogeneity

Note that the propensity of an individual to engage in introspection is a function of, among others, its tolerance for ambiguity (i.e. dissonance) and its sensitivity to the technological disruption of routines. These variables are presumed to be dependent on an individual's *personality*. Specifically, the inherited personality traits of an individual explain the degree to which he/she has a high need-for-cognition (Cacioppo, Petty, Feinstein, & Jarvis, 1996), is open to novel experiences or feels threatened quickly (Roccas, Sagiv, Schwartz, & Knafo, 2002).

2.3.5 Meso-Level Drivers of Belief System Change

Meso-level drivers of belief change affect groups of agents at a time. The meso-level drivers included in the ECBCS model are social influence processes and media exposure (see Figure 11).

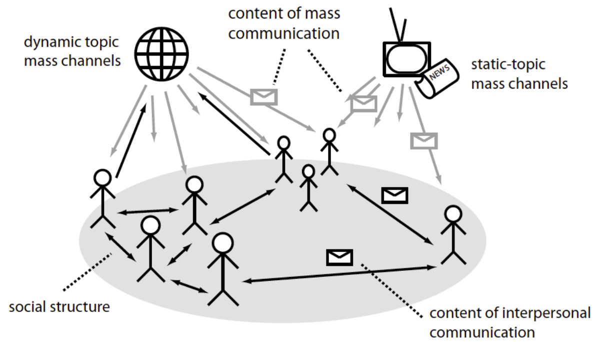


Figure 11. *Meso-Level Communication Processes in Agent Population (taken from Thiriot & Kant, 2008, p. 7, fig. 2).*

2.3.5.1 Social Influence Processes: General Characteristics

Humans are highly dependent upon frequent social contact for ensuring and maintaining a state of psychological well-being (see e.g. Haidt, 2012). Social interaction forms a crucial means to providing individuals with an identity, a sense of meaning, and understanding of reality (Friedkin & Johnsen, 1990). It comes to no surprise, then, that the content and configuration of belief systems are largely determined by *social influence processes* (Flache et al., 2017; Haidt & Bjorklund, 2007). Social influence processes refer to the changes in an individual's beliefs resulting from what other people do or say (Friedkin & Johnsen, 1990; McDonald & Crandall, 2015).

Social Network Theory (SNT) provides a useful perspective on how autonomous individuals combine and influence one another as to create enduring, and functioning societies (Borgatti, Mehra, Brass, & Labianca, 2009). SNT states that individuals are embedded in social networks. The structure of these networks determines how information may percolate through a social network. The positions people hold within these networks ultimately determines the flow of information to which any distinct person is exposed (Centola, 2015; Homer-Dixon et al., 2013). As noted before, belief systems are formed and updated according to the information an individual receives. This implies that the topology of a social networks affects the structure of the belief systems that reside within the minds of the actors that constitute the network (see e.g. Amblard & Deffuant, 2004; Centola, 2015).

2.3.5.2 *Social Influence Processes: Hot Interaction*

> The following section describes **link 7** in the non-formal model of belief system change (see Figure 5, Appendix 2).

Individuals seek to validate their beliefs of the world by comparing them with those of their peers (Homer-Dixon et al., 2013). As a consequence, individuals that frequently interact tend to mutually adapt their belief systems; which essentially means that they become to think more alike. This process is referred to as the *assimilation* of beliefs. The assimilation of affective beliefs is presumed to happen mainly through a process of *emotional contagion*. Emotional contagion refers to the way people 'catch' other people's emotions during social interaction (Hatfield et al., 1993). 18/11/2019 11:37:00The information embedded within emotional contagion is processed via the hot route. When individuals communicate with each other in an enthusiastic, passionate and/or emotional way, it is referred to as *hot interaction*.

Not everyone is equally motivated to assimilate their beliefs with those of others (Sherif & Hovland, 1961). Generally, similarity of beliefs correlates positively with the degree of belief assimilation (Dandekar, Goel, & Lee, 2013). Thus, the strength of assimilation is biased by the degree to which individuals feel that they share similar beliefs; this phenomenon is referred to as *biased assimilation*.

With regards to the structure of social networks, humans tend to organize themselves in groups of individuals that are similar to one another (Centola et al., 2007; Dandekar et al., 2013; Flache et al., 2017; Homer-Dixon et al., 2013; McPherson, Smith-Lovin, & Cook, 2001). In order to avoid psychological distress, individuals whose views are, or become, too dissimilar from the dominant views within a particular group will be motivated to split from that group and affiliate with other people that think and feel more like themselves (Homer-Dixon et al., 2013). This phenomenon is referred to as *homophily*. Hence, group formation follows the similarity of belief systems, and the subsequent social interactions within these groups leads people to become more alike through the biased assimilation of beliefs (Homer-Dixon et al., 2013).

Another relevant social influence process is *differentiation*. Differentiation describes how individuals can become *more dissimilar* through social interaction. Specifically, individuals that hold highly divergent views can come to negative evaluate one another, which motivates them to increase the psychological distance between them (Flache, 2018). To agree is to connect with someone; doing this with a person that is not considered to be similar to oneself may trigger uncertainty with regards to one's social identity which can be threatening (Lemaine, 1974). This process of 'hostile' differentiation is referred to as *repulsion*. Hence, it is presumed that agents holding (strongly) dissimilar views will tend to engage in repulsion during social interaction. Note that on a group-level scale, assimilation leads to intra-group similarities, whereas repulsion leads to inter-group differences (Hornsey, 2008).

Individuals may also experience, to varying degrees, the need to differentiate oneself from peers as to ensure the uniqueness of their personae (Leonardelli, Pickett, & Brewer, 2010). Specifically, people seek to establish and maintain a sense of self-distinctiveness because perceptions of extreme similarity or dissimilarity to others are experienced as unpleasant (Snyder & Lopez, 2002). This drive for uniqueness may serve to increase an individual's chances of procreation within a competitive social environment. It does so by enhancing one's ability to obtain social recognition through 'standing out from the crowd' (Lemaine, 1974). Note that the need for individuation competes with an opposing force, namely that of the need for affiliation and/or inclusion (Leonardelli et al., 2010). This balancing-act is referred to as the drive for attaining and/or ensuring an *optimal distinctiveness* (Leonardelli et al., 2010). Table 5 presents an overview of the two types of differentiation tactics that can be applied by agents during social interaction.

Table 5. *Overview of Social Differentiation Phenomena.*

Differentiation Type	Hostility	Theory
Repulsion	Hostile	Cognitive Dissonance Theory Social Balance Theory Social Identity Theory Self-Categorization Theory
Individuation	Non-hostile	Uniqueness Theory Optimal Distinctiveness Theory

On the basis of Social Judgement Theory (SJT; Sherif & Hovland, 1961), it is presumed that individuals assimilate their views with those of another person if the communicated beliefs fall within a zone of 'non-commitment' (i.e. *the goldilocks zone*). When this happens, it means that the beliefs of a sender are not too different, nor too similar to those of a receiver. In other words, the convergence of beliefs is strongest when beliefs are 'optimally' dissimilar. If beliefs are (very) similar, they fall within the acceptance zone (i.e. *the similarity zone*). Belief-convergence is generally modest in this case, since beliefs were already very similar prior to interaction. When beliefs are almost identical, an individual may feel the need to differentiate from a source as to ensure clear boundaries with regards to one's own identity (Leonardelli et al., 2010). Beliefs that are too different from one's own may fall within the rejection zone (i.e. *the disregard zone*). Beliefs that fall within the rejection zone are disregarded and ignored. Lastly, beliefs that are extremely different may fall in the repulsion zone (i.e. *the polarity zone*). When this happens, an individual may be motivated to increase the dissimilarity of its beliefs with those of an interaction partner (i.e. engage in repulsion). Table 6 provides a descriptive overview of the four interaction zones.

Table 6. *Overview and Description of Interaction Zones and Related Interaction Outcomes.*

Zone	Description	Interaction outcome
Similarity	Agents hold very similar beliefs; this may lead to the need to slightly move away from each other's viewpoints as to ensure individuality and maintain a quality or status of 'uniqueness' in the eyes of peers.	Individuation
Goldilocks	Agents hold beliefs that are similar, but not too similar. Agents are interested in one another and are motivated to listen to and understand each other.	Assimilation
Disregard	Agents are too dissimilar in the beliefs they hold for them to interact.	Ignorance
Polarity	Agents hold extremely dissimilar beliefs. Agents find it too hard to ignore one another and are motivated to fight for and defend their beliefs.	Repulsion

The social influence processes described throughout this section refer to *interpersonal* or *bilateral* interactions; that is, between pairs of individuals. A comprehensive modelling representation of belief change should also include a formalization of *multilateral* influence processes. Multilateral social influence represents a form of communication between an individual and the social group to which it belongs (Flache & Macy, 2011). One form of multilateral influence is coined *local conformity pressure*, or peer pressure (Flache & Macy, 2011). Such local conformity pressure involves the expectations people hold of how their views are likely to be evaluated by peers. Local majority pressure biases belief change in favour of the dominant views that exist within a particular group (Flache & Macy, 2011). Local majority pressure can be thought of as the perceived need to conform to a social group's subculture.

Lastly, it is important to consider the tendency of people to proselytize strongly held beliefs (Kinzig et al., 2013). Hence, the beliefs people discuss with one another during hot interaction are not selected randomly. Rather, the more extreme an individual's belief, the more likely it constitutes the topic of a passionate dialogue.

2.3.5.3 *Social Influence Processes: Cold Interaction*

> The following section describes **link 8** in the non-formal model of belief system change (see Figure 5, Appendix 2).

Communication between individuals that is about facts is referred to as *cold interaction*. The reason for this is that the information embedded in such factual communication is presumably processed via the cold cognitive route (see Figure 6) (Wolf et al., 2015).

Individuals continuously experience events on a first-hand account during their daily routines. The majority of these events go by unnoticed because they are not interesting enough. However, some of these events are surprising, and therefore interesting. Individuals are fundamentally driven to understand, explain, and share information with their social contacts about such curiosity-sparking events (Klein, Moon, & Hoffman, 2006; Kramer, 2016; Silvia & Kashdan, 2009). Events are surprising when they are moderately counter-intuitive or unexpected (Dimulescu & Dessalles, 2009). This implies that whether an event is perceived as surprising, or not, depends on the actual state of one's factual beliefs. In other words, not all events are perceived in the same way by all individuals. Moreover, an event once considered surprising may not surprise the same individual a second time due to updated factual beliefs.

As noted, individuals share the factual information they obtain from perceiving surprising events with their social contacts. As long as receivers of such information are also surprised, then the information spreads through a social network. This process of passing on x^{th}-hand factual information throughout a social network is referred to as *word-of-mouth*.

2.3.5.4 *Social Influence Processes: Social Media Interaction*

> The following section describes **link 7** in the non-formal model of belief system change (see Figure 5, Appendix 2).

Social media enables people to instantaneously communicate with one another regardless of their spatial distance. Moreover, the widespread adoption of smart mobile technology enables people to do so at all times. Social media platforms provide people with information about public affairs and offer an online space for them to express their beliefs and engage in discussions with others (Kim, Hsu, & de

Zúñiga, 2013). In doing so, social media democratizes a one-to-many form of communication; where anyone is potentially able to reach out to large, and diverse swaths of people.

These features of social media platforms increase the exposure of individuals to diverse or heterogeneous beliefs (Kim et al., 2013). On the one hand, the exposure to diversity may help individuals comprehend the rationale and motivation behind different perspectives and become accustomed to encountering dissimilar opinions. This should foster the emergence of mutual understanding and tolerance (Kim et al., 2013). On the contrary exposure to (radically) different views may trigger a process of self-defensive repulsion.

Furthermore, the growing abundance of media platforms allows people to engage in ever more sophisticated forms of *selective exposure* (Stroud, 2010). Selective exposure occurs when individuals actively seek out congenial information while avoiding challenging, or uncomfortable viewpoints (Kim et al., 2013). A large body of research indicates that people often seek out information that is congruent with the beliefs they hold (Stroud, 2010). When individuals use social media to preferentially expose themselves to like-minded others and react defensively or hostile to incongruent views, this may lead to an increasingly fragmented and polarized society (Kim et al., 2013).

2.3.5.5 Social Influence Processes: Mediators & Moderators

The following section describes **links 7 and 8** in the non-formal model of belief system change (see Figure 5, Appendix 2).

The social influence processes described in the previous sections are likely to be affected by a myriad of factors (Sobkowicz, 2018), amongst which: social status differences between interacting individuals, the degree of trust that exists between interacting individuals, and individual differences in personality.

Social status differentials are presumed to influence belief-convergence during social interaction. Specifically, the higher the status discrepancy, the more asymmetric the convergence of beliefs between interactants is presumed to be. Social status can be defined as the degree of influence one possesses over resource allocations, conflicts, and decisions within a social group (Cheng, Tracy, & Henrich, 2010). High-status people are generally perceived as role models, or leaders, with a disproportionate influence on group functioning and thinking (Langner, Hennigs, & Wiedmann, 2013). Hence, an individual with a lower social status is presumed to be persuaded more easily than someone with a higher status (Horcajo, Petty, & Briñol, 2010).

Another variable that is presumed to affect belief-convergence during social interaction is trust. Trust is a property of collective units (dyads, groups, collectives); it is applicable only to the relations amongst people (Lewis & Weigert, 1985). The function of trust is, essentially, to reduce complexity. Trust allows social interactions to proceed on a simple, predictable and confident basis. In the absence of trust, the startling complexity posed by contingent futures would paralyze action, induce confusion and bring about social chaos (Lewis & Weigert, 1985). Distrust also reduces complexity by dictating courses of action based on suspicion, monitoring, and implementation of safeguards (Lewis & Weigert, 1985). Hence, trust and distrust serve the same function, but lead to different kinds of social systems; the former breeds solidarity, the latter atomism (Lewis & Weigert, 1985).

Trust has been found to develop easier amongst people that are familiar with one another, and that appear similar to each other (Stolle, Soroka, & Johnston, 2008). Thus, building trust involves a degree of cognitive familiarity and emotional connection with the object of trust (Lewis & Weigert, 1985). This implies that frequent and positive social interaction breeds trust. Trusted others serve as 'informational' anchors for orienting the formation, or revision of one's beliefs (Fornara, Pattitoni, Mura, & Strazzera, 2016). In other words, the convergence of beliefs is positively influenced by the trustworthiness that interactants ascribe to one another.

Furthermore, it is presumed that the interaction-decision is affected by the personality traits of the interactants (Asendorpf & Wilpers, 1998). Personality *traits* may be defined as *"...stylistic and habitual patterns of cognition, affect and behaviour"* (Emmons, 1989, p. 32). A *personality* may be defined as *"...a high-level abstraction encompassing sets of stable dispositions towards action and towards belief and attitude formation"* (Pianesi, Mana, Cappelletti, Lepri, & Zancanaro, 2008, p. 53). A large body of research indicates that human personality can be expressed in five dimensions: Neuroticism, Extraversion, Openness to Experience, Agreeableness, and Conscientiousness (Soldz & Vaillant, 1999; Zillig, Hemenover, & Dienstbier, 2002).

People with relatively high levels of neuroticism are more insecure and anxious (Pianesi et al., 2008); it is therefore presumed that these individuals react more hostile towards people that hold divergent views. In other words, anxious individuals will be quicker to perceive divergent beliefs as threatening and are therefore suspected to engage in repulsion more often. People with high levels of extraversion are sociable and assertive, indicating that these people might have a narrower disregard zone than introverts (Kim et al., 2013). Extraverts will therefore decide to interact more often than introverts. Individuals that exhibit high openness to experience are intellectual, insightful and open-minded (Pianesi et al., 2008), which means that they might be more tolerant and understanding of divergent perspectives. Individuals that are characterized by high levels of agreeableness are friendly, compassionate and cooperative (Pianesi et al., 2008); these individuals may also exhibit a higher tolerance of divergent perspectives. Individuals with a higher tolerance of divergent beliefs will engage in repulsion less often.

Lastly, factors such as one's experienced uncertainty, or the extremity of one's beliefs may interfere with belief-convergence. The extremity of a belief indicates the importance of that belief to one's self-concept. Belief central to the self-concept are more resistant to change. This phenomenon is referred to as *ego-involvement* (Petty, Cacioppo, & Haugtvedt, 1992). Thus, it is presumed that highly cherished or detested (i.e. extreme) values and/or strong factual beliefs exhibit a greater resistance to change. Furthermore, experienced uncertainty, or doubt, with regards to the status of one's beliefs triggers a need for obtaining information as to restore a sense of normality and stability (Lachlan, Spence, & Seeger, 2009). Hence, an individual that experiences high levels of uncertainty will presumably be more likely to revise her beliefs in reaction to incoming information.

2.3.5.6 Media Exposure

The following section describes **links 9 and 10** in the non-formal model of belief system change (see Figure 5, Appendix 2).

Media play an important role in an individual's acquisition of meaningful knowledge about the non-immediate world (Jackob, 2010; Roskos-Ewoldsen, Davies, & Roskos-

Ewoldsen, 2004). Hence, media exposure forms a potentially powerful determinant of the content and configuration of one's belief system (Iyengar & Hahn, 2009; Kim et al., 2013; Roskos-Ewoldsen et al., 2004; Stroud, 2010). Media are considered a meso-level driver of belief change because they are able to simultaneously affect multiple individuals, but are unlikely to do so in case of an entire population.

The current study distinguishes three types of media: (i) mass media, (ii) niche media, and (iii) expert media. A description of these media types can be found in Table 7.

Table 7. *Description of Media Types.*

Media type	Description
Mass	Mass, or mainstream, media represent traditional and relatively centralized media systems. Mass media are managed by large (public or private) corporations that to aim to reach the widest possible audience. Mainstream media is an inclusive, not a niche-targeted, channel (Tsfati & Peri, 2006).
Niche	Niche, or alternative, media represent dispersed specialized outlets with smaller audiences (Tsfati & Peri, 2006). Whereas mainstream media are owned by large corporations (be they publicly or privately owned), alternative media are small-scale news productions (Tsfati & Peri, 2006). Another distinction between mass and niche media is that the former is embedded into power, whereas the latter reflects peripheral, often radical, views that are seldom broadcasted through mainstream channels (Tsfati & Peri, 2006).
Expert	Expert, or technical, media represent high-quality media objects such as scientific reports, research papers and/or investigative journalism (e.g. informational longreads).

People may be exposed to media items either incidentally or intentionally. In case of intentional exposure, one may exert control over what media type and content one is exposed to. Hence, intentional exposure permits *selective exposure*, whereas incidental exposure does not. With regards to media type selection, it is presumed that non-conformist and/or conspiracy-thinkers are more likely to select niche media. Furthermore, intelligent people with a high need-for-cognition (Cacioppo et al., 1996) are presumed to select expert media relatively more often than other people do.

It is assumed that people who distrust mainstream media, are more likely to select niche media when seeking for mediated information (Tsfati & Peri, 2006). People may start to distrust mass media when they become in some way susceptible to forms of conspiracy thinking. Conspiracy thinking relates to thought patterns that in some way attempt to explain real-world phenomena as manifestations of a powerful conspirators' self-serving intentions (Heins, 2007). Conspiracy thinkers tend to actively distrust mainstream media channels, because they distrust the broadcasting corporations responsible for managing those outlets. Conspiracy thinkers may belief that mass media corporations pursue malevolent self-serving agendas, and that they do so by exploiting their power to control, or indoctrinate the masses (Heins, 2007).

Moreover, people that value individualism, independence and/or self-direction, may prefer niche media over mass media. Such non-conformist individuals may experience a particular positive emotional intensity or excitement from distancing themselves from mainstream society (Heins, 2007). Since mass media are considered mainstream, non-conformists are presumed to avoid these outlets.

Individuals may exhibit varying degrees of susceptibility with regards to the persuasions embedded in media content. This susceptibility is, amongst others, a function of one's experienced dependence on media as a provider of information (Jackob, 2010). At times someone may have, or perceive, no functional alternatives to media. A functional alternative to media is obtaining information through social interaction. This implies that someone socially isolated will be more dependent upon media for obtaining information and making sense of the world, than someone that is more socially connected.

Another determinant of media dependency is perceived threat and/or experienced uncertainty (Lachlan et al., 2009). Fear, confusion and uncertainty trigger a fundamental need in humans to acquire information in order to restore a sense of control and normality (Heath & Gay, 1997). When the most salient aspects of one's environment become ambiguous and/or difficult to understand, people become especially dependent on mediated information (Ball-Rokeach, 1985; Ball-Rokeach & DeFleur, 1976). This implies that in times of uncertainty and systemic instability, people's media dependency increases.

Media types may also differ in the way they frame and present their content to a recipient. The diversification and democratization of media incentivizes media outlets to cater their content to viewers' beliefs in order to please and retain them (Mullainathan & Shleifer, 2005). This phenomenon is referred to as *media bias* and works hand in hand with selective exposure to increase intergroup differences in viewpoints. A form of media bias that is especially present in niche media is the *filter bubble effect*. Alternative, or niche, media outlets have been implementing recommender systems, and search- or feed-ranking algorithms that enable sophisticated matching of content with the belief systems of viewers (Bozdag & van den Hoven, 2015). Hence, it is presumed that niche and mass media can both be biased in terms of providing viewers with congenial content, but that niche media tend to exhibit a stronger bias due to this filter bubble phenomenon.

Furthermore, it is presumed that mass media tend to cultivate attitudes and values that are already present in a culture (Gerbner, Gross, Morgan, & Signorielli, 1986), whereas niche media tend to cultivate forms of cultural deviance. The cultural bias of mass media refers to their propensity to select and frame messages in favour of cultural viewpoints. That is, if a majority within a population cherishes (detests) a particular value, mass media will tend to broadcast positive (negative) viewpoints related to that value.

The information communicated by media channels serves to update the understanding of viewers with regards to the actual state of the world. It is presumed that expert media help viewers or readers factually understand how the world is. Niche and mass media are assumed to infuse their reporting with emotional cues as to capture and retain the attention of viewers (Soroka & McAdams, 2015). In doing so, niche and mass media often present opiniated reports, or discussions of what is happening in the world. As a consequence, niche and mass media are presumed to appeal predominantly to the hot cognitive route, whereas expert media activate the cold route.

Human brains are innately predisposed to give greater weight to negative entities. This phenomenon is referred to as *negativity bias* (Rozin & Royzman, 2001) or *salience bias* (Tversky & Kahneman, 1974). Due to this negativity bias, depictions of violence or other forms of human suffering are strong attention grabbers (Soroka & McAdams, 2015). Niche and mass media tend to exploit this negativity bias in their reporting as is exemplified by the well-known phrase *"if it bleeds, it leads"*. Cultivation

Theory postulates that this leads heavy users of (mass and niche) media to perceive the world as more threatening or dangerous than it actually is (Gerbner et al., 1986); a phenomenon referred to as the *Mean World Syndrome*.

2.3.6 Macro-Level Drivers of Belief System Change

2.3.6.1 Culturalization

The following section describes **links 4 and 5** in the non-formal model of belief system change (see Figure 5, Appendix 2).

Culturalization is the process by which cultural transmission occurs throughout one's lifetime. Culturalization is considered a macro-level driver of belief change because it influences, albeit to varying degrees, an entire population of agents at any given time.

It is presumed that people vary in their proclivity to be instrumentally and/or intrinsically motivated to conform to a particular culture's standards. For example, non-conformists are generally less inclined to follow norms either instrumentally, intrinsically or both (Gelfand & Jackson, 2016). Furthermore, situational factors such as the perceived instability of environmental conditions and/or experienced uncertainty leads people to become more conformist to prevailing (cultural) norms (Gelfand & Jackson, 2016; Hogg, 2007).

It is hypothesized that culture emerges from the inferences that people make, and the consequent expectations they have, with regards to other people's *viewpoints*. A viewpoint refers here to a particular position on a value's importance-spectrum (see Figure 12 or Figure 13). People are presumed to hold a mental representation of the distribution of viewpoints within a population (henceforth referred to as *subjective viewpoint-distributions*; see left-hand side of Figure 12). That is, every person is to some extent aware of her own position on a value's importance-spectrum, as well as those of *cultural peers*. Cultural peers refers here to people belonging to the same cultural *reference group*. A reference group is defined as any group that an individual sees as a source for its identity (Goldsmith & Thomas, 2003).

People construct and update their subjective viewpoint-distributions based on the opinions expressed by others. As long as people are saying what they are truly thinking, subjective viewpoint-distributions will closely resemble the *actual* population viewpoint-distribution. What people collectively perceive as being the most common viewpoint with respect to some value is referred to as a *cultural standard*. For instance, if everyone believes that *"a large majority of people thinks that environmental sustainability is very important"*, then valuing environmental sustainability becomes a cultural standard.

This conceptualization allows culture to feed back on the viewpoints on which it is based (see right side of Figure 12). Specifically, culture is able to constrain its own change by pulling back non-normal, or 'outlier', views towards the local high-density peaks that are present within a population viewpoint-distribution. Figure 12 visualizes this culturalization process.

As can be seen in the right-hand side of Figure 12, the observed shape of a population viewpoint-distribution can be thought of as the aggregation of all subjective viewpoint-distributions. In nations that promote unconstrained freedom of speech, the aggregated viewpoint-distribution is practically the same as the *actual* population viewpoint-distribution. The yellow dots (to be observed in the right side of Figure 12) represent individuals that are being influenced by culture to conform to the views of a (local) majority. Culture is represented by the red arrows; it is the force that draws individual viewpoints closer towards each other.

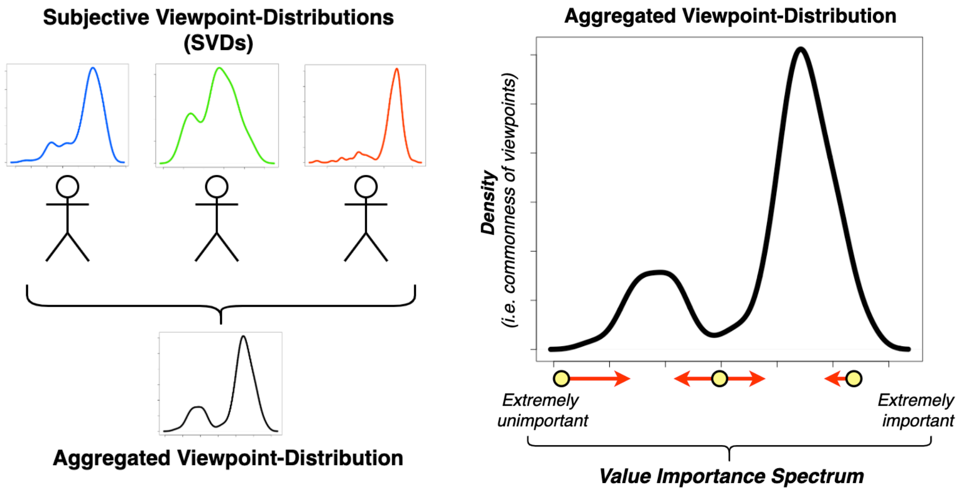


Figure 12. *Visualization of Culturalization.*

2.3.7 *Omni-Level Drivers of Belief System Change*

2.3.7.1 *Technological Change*

> The following section describes **links 1 and 2** in the non-formal model of belief system change (see Figure 5, Appendix 2).

A model of belief system change must acknowledge the omni-level presence of the influence of technological change (see Table 8). Technological change may affect people's belief systems directly through micro-level processes. It may also function as a catalyst for the influence of direct drivers residing on higher levels such as enabling the digitization of social interaction processes.

Table 8. *Omni-Level Presence of Technological Change as a Driver or Catalyst of Belief System Change Processes.*

Scale	Mechanism	Examples
Micro	Technologies alter individual perceptions of reality and of the self through the disruption of individual routines.	- Smartphones - Gamification - Augmented reality
Meso	Technologies alter people's social reality through far-reaching digitization of social interaction processes.	- Social media platforms (e.g. Facebook, Twitter etc.) - Digital telecommunication software (e.g. Skype)
Macro	Technologies trigger structural changes in the organization of societies (Chai, 2009).	- Industrialization - Bureaucratization - Commercialization

2.4 Non-Formal Model of Belief System Change

Figure 5 in Appendix 2 shows the conceptual model of belief system change within an energy-system's context. Chapter #3 describes how the conceptual model is formalized and implemented within a modelling environment.

2.5 Chapter 2: Recapitulation

The following key takeaways summarize the content of Chapter #2:

- Values are affective beliefs about preferred end-states of reality. Values serve to *guide* and *justify* actions over a wide range (in terms of diversity) of situations.

- Values may influence behaviour through the formation of attitudes. Attitudes constitute one of several determinants that shape behavioural intentions. Intentions form a strong predictor of an individual's behaviour.

- Values interact with knowledge (i.e. *factual beliefs*) to form attitudes. Factual beliefs are about *how the world is*. Specifically, they are defined here as the subjective probability that some factual statement about reality is valid. Hence, factual beliefs are not about what is important or desirable in life.

- Values are most likely to affect decision making (i.e. behaviour) when a decision maker is faced with a non-routine decision. Non-routine decisions are characterized as being novel and unfamiliar in the eyes of the decision maker. The adoption of a CET is considered a non-routine decision. Hence, values are likely to influence a consumer's decision to adopt a CET.

- Attitudes are defined here as *evaluations* of specific objects and/or entities. Attitudes contain a *cognitive* component (what is the object or entity?) an *affective* component (given what I know about the object or entity, how do I feel about it?), and a *behavioural* component (given what I know and feel about the object or entity, how do I orchestrate my actions towards it?).

- Attitudes may serve *utilitarian* or *symbolic* functions for the individual that holds them. In a utilitarian sense, attitudes function as heuristics that instruct an individual on whether to *approach* or *avoid* a particular object or entity. In a symbolic sense, attitudes may serve an individual as a way to express the values it cherishes (i.e. *value-expressive function*) or to accentuate or manage its social identity or image (i.e. *social-adjustive function*).

- Factual and affective beliefs are logically and functionally interrelated, forming a structure that is referred to as a *belief system*.

- In general, belief systems are shaped by an individual's experiences with the world. However, one's experiences *do not fully determine* the content of one's belief system (Chai, 2009). This implies that humans, to a varying extent, engage in creative and/or selective assimilation of their beliefs with that which they experience. An example of this is *motivated reasoning* which describes how people tend to disregard information that does not harmonize with their existing beliefs. A belief system may change when it is (repeatedly) exposed to information that *contradicts*, or is *incompatible* with its contents.

Individuals are motivated to avoid belief system change as it constitutes a confusing, uncertain, and potentially frightening experience.

- A collection of interacting belief systems gives rise to the emergence of *culture*. Culture can be thought of as the belief system of a society. Culture influences individual belief systems by homogenizing their configuration and content. This implies that change within individual belief systems is biased towards cultural standards. Specifically, culture makes people think more alike. Culture serves a social group by guiding the behaviours and thoughts of its members on the basis of collectively agreed upon expectations and rules (Fershtman, Gneezy, & Hoffman, 2011). Individuals are innately predisposed to follow and enforce cultural conformity.

- During deliberate decision making and problem-solving, values undergo a process of practical *testing*, and potential *revision* in light of the consequences of their guidance. Deliberate decision making happens when decision makers are faced with unforeseen and unfamiliar situations. It is presumed that as socio-technical-ecological systems become more unstable, people become more frequently exposed to such unforeseen and unfamiliar situations. Hence, system instability disrupts individual belief systems and thereby drives value change.

- Key drivers of belief system change, besides culture and system instability, are: *introspection*, *technological change*, *social influence processes*, and *media exposure*. These drivers are not mutually exclusive as their effects on an individual's beliefs often interact with one another.

3 Model Formalization & Implementation

The following chapter describes how the conceptual model of belief system change is formalized and implemented within a modelling environment. Each process step within the overall simulation procedure is described using a combination of mathematical equations, pseudocode, flow-charts and/or chronological narratives. Table 9 (Appendix 1) provides an overview and description of the different styles of notation used throughout the current chapter. When reading through Chapter #3 it should become clear *what* each algorithm does, as well as *why*, *how* and *when* it does so.

3.1 General Model Characteristics

3.1.1 *Entities*

The ECBCS model contains three types of entities: (i) energy consumers, (ii) social ties and (iii) energy technologies (see Table 16 in Appendix 1). Note that energy consumers are considered to represent households, not individuals. The first and second entities are represented as agents, the third as an object. Agents are capable of engaging in independent decision-making processes and may interact with one another, their environments and objects. Objects, on the contrary, are passive entities that do not engage in any activities that require a form of agency. Hence, objects cannot be described by actions and/or interactions.

3.1.2 *Temporal & Spatial Resolution*

A tick, or timestep, within the ECBCS model represents a *round of interaction*. Hence, a tick does not explicitly represent a temporal unit from the International System of Units per se (i.e. seconds, hours, days, weeks etc.). A round of interaction should be understood as an abstract unit representing the flow and/or development of information within and across an artificial society. Moreover, spatial scales are not explicitly represented within the ECBCS model. The only spatial functionality the model offers is the visualization of the social distance between agents (i.e. the social network topology).

3.1.3 *Basic Simulation Assumptions*

For an overview of assumptions present within the ECBCS model, the interested reader is referred to Appendix 3.

3.1.4 *Process Overview & Scheduling*

Figure 1 (Appendix 2) depicts an overview of sub-models included in the ECBCS model and the order in which they are executed over the course of a given timestep. The sub-models are described in full detail throughout Section 3.2.

3.1.5 *Setup & Initial Settings*

For an overview and argumentation of initial (default) model settings, the interested reader is referred to Appendix 3.

3.2 Belief System Model

Agent belief systems are presumed to consist of two subsystems: an affective (value) system and a factual (knowledge) system. Attitudes are formed through the interaction between these two subsystems (see Figure 6). The sections 3.2.5 and 3.2.6 provide a detailed description of how the attitude formation process is executed.

3.2.1 *Value System Model: Formalization*

Each agent is equipped with its own unique value system. A value system is represented by a list consisting of nine values (v_i), each representing a BVT value type (see Table 9). The nine values are operationalized as decimal numbers ranging in a continuous fashion from 0 to 1. Where 0 represents an absolute rejection of the importance of a particular value, and 1 signifies an extremely high importance ascribed to a value (see Table 9); thus providing a natural space for value level variability and polarization.

Table 9. *Description of Value Levels and Related Importance and Emotional Qualities.*

Value Level	Importance Level	Emotional Level	Emotional Valence
0	Absolutely not important	Emotionally strong	Negative
0.5	Indifferent	Emotionally weak	Neutral
1	Absolutely important	Emotionally strong	Positive

This model representation allows ranking the values in order of importance. Moreover, it allows for representing the emotional, or affective, strength of a particular value as its absolute deviation from the neutral position (0.5). For instance, a value (v), e.g. "Benevolence", with a level of 0.10 is classified as unimportant ($v < 0.5$) and emotionally strong ($|v - 0.5| = 0.4$); which is to say that an agent holding such a value will feel a (strong) resentment towards the idea of valuing benevolence. Figure 13 presents a visualization of the current formalization of values.

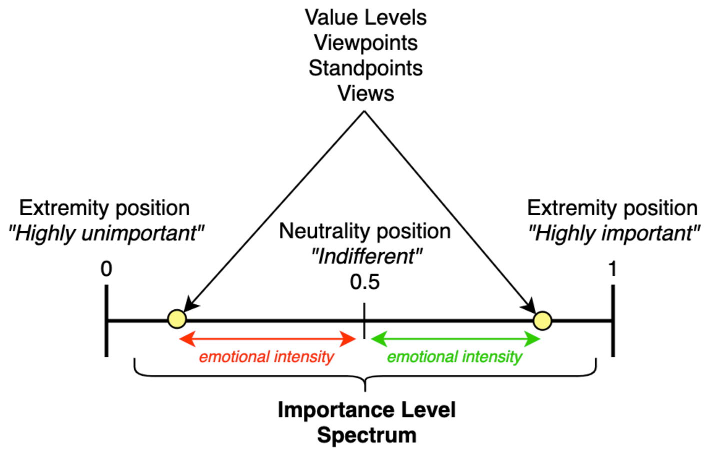


Figure 13. *Visual Representation of Value Formalization.*

This representation of values also enables one to determine the degree of value system similarity between pairs of agents through calculating Euclidian distances between value systems (see Section 3.7). Quantifying the similarity of value systems between agents, and groups of agents allows for modelling social phenomena such as homophily and xenophobia.

Lastly, the current representation of values allows for the calculation of covariance (or correlation) matrices (see Equation #1). These matrices provide insight into the inter-value relationships as described by the BVT.

$$\begin{bmatrix} \sigma_{00}^2 & \sigma_{01}^2 & \cdots & \sigma_{09}^2 \\ \sigma_{10}^2 & \sigma_{11}^2 & \cdots & \sigma_{19}^2 \\ \vdots & \vdots & \ddots & \vdots \\ \sigma_{90}^2 & \sigma_{91}^2 & \cdots & \sigma_{99}^2 \end{bmatrix} \qquad \begin{bmatrix} \rho_{00} & \rho_{01} & \cdots & \rho_{09} \\ \rho_{10} & \rho_{11} & \cdots & \rho_{19} \\ \vdots & \vdots & \ddots & \vdots \\ \rho_{90} & \rho_{91} & \cdots & \rho_{99} \end{bmatrix} \tag{1}$$

3.2.2 *Value System Model: Calibration*

The concept of *social milieus* facilitates modelling agents that represent members of distinct social groups within artificial populations. Specifically, social milieus signify distinct homogeneous groups of individuals within a given population who share similar value systems and aspirations in life (Wittman, 2008). Hence, social milieus help to specify an agent's values and the relative importance it ascribes to these values (Wittman, 2008).

Calibration of agent value systems is done using the social milieus presented by the WIN-model (WIN: Waarden In Nederland) (Hessing-Couvret & Reuling, 2002) and relevant statistics found in Aalbers (2006). The WIN-model is chosen over other models of Dutch culture (for a brief overview see e.g. Boogaard, Oosting, & Bock, 2006) because it is predominantly based on the BVT. The decision to apply the WIN-model seems justified given that the BVT constitutes an important part of the current theoretical framework.

The WIN-model distinguishes eight social milieus or, stated differently, *value segments* (see Table 3 in Appendix 1). A value segment represents a set, or cluster of values that is cherished (or detested) amongst members of a particular societal segment (Boogaard et al., 2006). Just like the BVT framework (see e.g. Schwartz, 2012), the WIN-model places these value segments within a two-dimensional framework. The two axes of the WIN-model are: conservation vs progression, and self-orientedness vs other-orientedness (see Figure 3 in Appendix 2).

Subsequently, linkages are made between the BVT value types and the WIN-segments. Specifically, qualitative descriptions of the WIN value segments presented in Aalbers (2006) are used to build so-called BVT Value Profiles (BVPs) for each segment (see Table 11). BVPs are lists that consist of nine discrete integers ranging from 1 to 5 that represent ranked scores, or 'importance levels', for each of the BVT value types.

An agent belonging to a particular WIN-segment is attributed a segment-specific BVP. The BVP is consequently transformed by drawing a pseudo-random decimal value from a normal distribution characterized by a mean ($\mu_{ValueLevel}$) and standard-deviation ($\sigma_{ValueLevel}$) for each individual value importance score (see Table 10). In doing so, a list with a length of nine integers consisting of {1,2,3,4,5} is mapped onto a list of nine decimals (X_i) ranging from $0 \leq X_i \leq 1$.

Table 10. *Calibration of Value Levels.*

Importance-Level	Score	$\mu_{ValueLevel}$	$\sigma_{ValueLevel}$
Very high	1	0.90	0.10
High	2	0.75	0.10
Medium	3	0.50	0.10
Low	4	0.25	0.10
Very low	5	0.10	0.10

i) Note that value levels are constrained to [0 … 1].
ii) Values for $\mu_{ValueLevel}$ and $\sigma_{ValueLevel}$ are not based on empirics; they are assumed.
iii) A 'value level' is the same as a viewpoint.

Applying a sampling procedure for the calibration of value levels introduces variance between the value systems of agents belonging to the same WIN-segment. This variance should account for the fact that although agents belong to the same WIN-segment, they are allowed to hold somewhat dissimilar value systems.

Table 11. *BVT Value Profiles for Each WIN-Segment and Representative Proportion of the Dutch Population.*

WIN-Segment	HED	STM	SD	UNI	BEN	CT	SEC	POW	ACH	%*
Broad minds	5	3	2	1	2	3	4	5	3	7
Socially minds	5	3	3	1	1	3	3	5	3	11
Caring faithfuls	4	4	4	2	1	1	2	4	5	13
Conservatives	3	4	5	3	3	1	1	3	4	17
Hedonists	1	2	3	5	4	3	2	2	3	8
Materialists	2	2	3	4	5	3	3	1	2	7
Professionals	3	2	1	2	3	5	3	2	1	9
Balanced minds	3	3	3	3	3	3	3	3	3	28

* = taken from Aalbers (2006).

The design, implementation and evaluation of the surveys required to empirically determine the BVPs for each of the WIN-segments lies beyond the scope of the current study. Instead, the BVPs are constructed on the basis of the author's expert judgment.

3.2.3 *Factual Belief System Model: Formalization*

A factual belief is formalized as a pair of decimal numbers (X_1, X_2), both with a continuous range of $0 \leq X_i \leq 1$. The first decimal number (X_1) represents a factual statement about how the world is (X_1 = Factual Statement), the second decimal number (X_2) represents an agent's experienced level of credence, or confidence, in a particular factual statement (X_2 = Confidence Weight). A factual statement is defined here as a falsifiable statement about how reality is.

Due to the nature of current study's topic, factual statements are about the performance of innovative CETs relative to the performance of technologies they aim to replace as part of the energy transition. Agents may, to the best of their knowledge, make factual statements about the comparative performance of CETs.

In order to decide on the types of energy technologies to include within the current study, it is useful to start with a categorization of household energy-related activities. Energy is used for a wide range of household activities that can be categorized into two broad domains, namely: 'home' and 'transport' energy-use (Poortinga et al., 2004). Transport energy-use refers to mobility (e.g. driving one's car or motorbike), whilst home energy-use refers to heating, ventilation, lighting and the use of household appliances (Poortinga et al., 2004). The current study splits the 'home' domain into two subdomains, namely: 'heating & cooling' and general 'power'. Thus, three energy consumption domains (e.g. mobility, heating & cooling, power) are used to cover the range of households' energy-related activities.

For each household consumption domain, a decision is made to include the most used (mainstream) technology as well as an innovative newcomer that forms a potential disruption to the carbon-rich status quo. The selection of energy technologies can be seen in Table 12.

Table 12. Selection of Energy Technologies for Each Household Consumption Domain.

Index	Domain	Technology	Type
1	Power	Photovoltaic (PV) Cell(s)*	Innovative
	Power	Grid Connection (GC)	Mainstream
2	Mobility	Battery Electric Vehicle (EV)	Innovative
	Mobility	Internal Combustion Engine Vehicle (ICEV)	Mainstream
3	Heating & Cooling	Heat Pump (HP)	Innovative
	Heating & Cooling	Natural Gas Boiler (NGB)	Mainstream

* = Stand-alone (off-grid) PV system.

Factual statements take on the form of *"The performance of technology X is lower/similar/higher than the performance of technology Y on attribute Z"*; where technology X and Y fall within the same energy consumption domain. Technology X is constrained to being innovative, technology Y to being mainstream. Table 13 shows the relative performance of each selected CET. Note that a lower or higher performance does not necessarily imply a *worse* or *better* performance; notions of 'good' or 'bad', 'better' or 'worse' are valuations, whereas 'lower' or 'higher' are factual statements.

The scores in Table 13 serve as very crude estimations of the performance differentials between energy technologies. However, the purpose of the current study is not to conduct thorough performance assessments of energy technologies. Hence, given the scope of the current study, the guesstimates in Table 13 provide a satisfactory calibration of relative CET performance levels.

It is presumed that PV holds a higher performance on purchasing cost than GC (IRENA, 2012); note that a higher performance refers to a *higher* purchasing cost. Moreover, EVs (Energysage, 2019a) and HPs (Renewable Energy Hub, 2019) are also presumed to exhibit a higher performance on purchasing cost than their mainstream counterparts.

With regards to operating cost, PVs are presumed to exhibit a lower performance since the electricity generated is practically free of charge (Energysage, 2019b). Although PV systems must be maintained and repaired over the span of their productive lifetimes, it is presumed that these costs do not outweigh those of consuming electricity via a grid connection. EVs also exhibit lower performance in terms of operating cost due to substantially lower fuelling costs and relatively low maintenance costs (Energysage, 2019a). Lastly, HPs are cheaper to run than their mainstream counterparts (i.e. NGBs); hence they also exhibit a lower performance in terms of operating cost (Renewable Energy Hub, 2019).

Whereas dwellings come equipped with a GC, PV systems must be installed, maintained and repaired. The relatively higher investment of time and effort required for PV systems render its performance to be lower on the comfort attribute. EVs exhibit a lower driving range than their ICEV counterparts; they also take longer to refuel (Energysage, 2019a). Hence, EVs also exhibit a lower performance in terms of comfort. Lastly, HPs are relatively difficult to install, so their comfort performance is presumed to be lower than that of NGBs (Renewable Energy Hub, 2019).

In terms of safety, PV systems and EVs are presumed to perform highly similar to their mainstream counterparts; GC and ICEVs, respectively. HPs are presumed to be more safe than combustion-driven NGBs (Renewable Energy Hub, 2019). With regards to the environmental performance of the CETs, all of them are presumed to outperform their mainstream counterparts. PV and HP are presumed to show higher performance on the autonomy attribute; since they both enable consumers to become self-reliant in terms of energy supply. EVs do not differ from ICEVs in this regard. Lastly, only PV systems are presumed to outperform their mainstream counterpart in terms of privacy as they allow users to privatize their electricity consumption data.

Table 13. *Relative Performance Scores for Each CET on Selected Attributes.*

Index	Attribute	PV	EV	HP
1	Purchasing cost	1	1	1
2	Operating cost	0	0	0
3	Comfort	0	0	0
4	Safety	0.5	0.5	1
5	Environment	1	1	1
6	Autonomy	1	0.5	1
7	Privacy	1	0.5	0.5

Note: a score of "1" represents "higher performance", "0.5" represents "similar performance" and "0" represents a "lower performance".

Within the ECBCS model, each CET is described by a list of attribute performance levels [$AttPerfList_{Actual}$] consisting of seven integers taking on one of the values {0, 0.5, 1}. The ECBCS model allows for plugging in other CETs as long as they are characterized by their own [$AttPerfList_{Actual}$].

The initial [$AttPerfList_{Actual}$] is subsequently transformed into a list consisting of seven decimals (X_i) ranging from $0 \leq X_i \leq 1$. This transformation is done by drawing pseudorandom decimal values for each initial performance level score from a normal distribution characterized by mean ($\mu_{AttPerf}$) and standard-deviation ($\sigma_{AttPerf}$) (see Table 14). This transformation is performed in order to account for the fact that differences in technology attribute performances vary on a continuous scale. Note that the current calibration procedure for attribute performance levels is not based on empirical evidence as this lies beyond the scope of the current study.

Table 14. *Calibration of Attribute Relative Performance Levels.*

Relative Performance	Score	$\mu_{AttPerf}$	$\sigma_{AttPerf}$
Lower	0	0.10	0.25
Similar	0.5	0.50	0.25
Higher	1	0.90	0.25

i) Note that calibrations of attribute performance levels are constrained to [0 … 1].
ii)The values for $\mu_{AttPerf}$ and $\sigma_{AttPerf}$ are not based on empirics; they are assumed.

The [$AttPerfList_{Actual}$] of a given CET represents the *actual* state of reality; it represents the objective performance of a CET on all seven attributes. Throughout the simulation, agents seek to uncover the attribute performance levels of each CET. Specifically, each agent holds its own mental copy (i.e. conception) of a CET's attribute performance list, which is labelled as [$AttPerfList_{FactualBelief}$] (see Figure 14). Agents update their [$AttPerfList_{FactualBelief}$] as they receives information from their environments. An agent's [$AttPerfList_{FactualBelief}$] is comprised of a list of $N_{Attributes}$ factual statements [$AttPerfList_{FactualStatement}$] and $N_{FactualStatements}$ confidence weights [$AttPerfList_{ConfidenceWeight}$]. Agents hold 3x lists of factual beliefs, one for each CET (i.e. 'PV', 'EV' and 'HP').

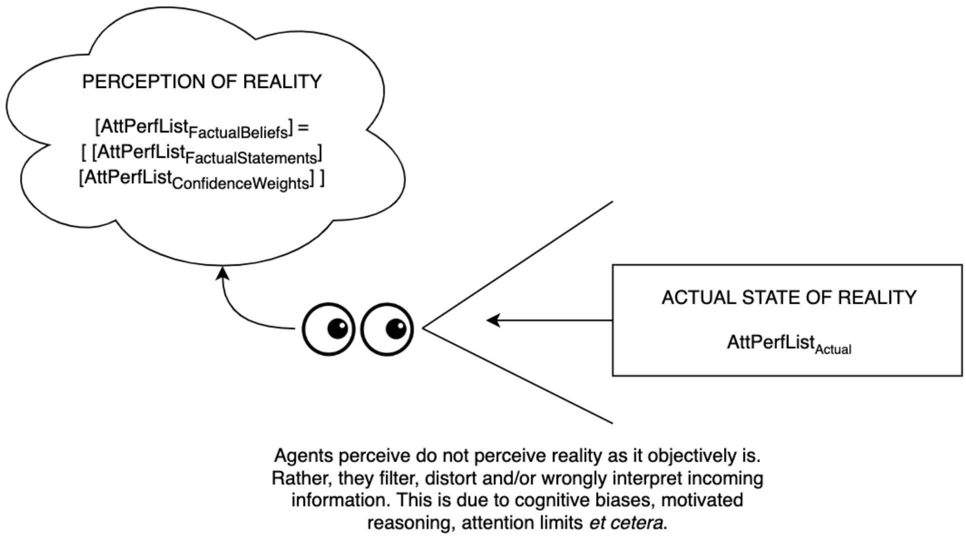


Figure 14. *Agent Perception of Reality.*

As noted, a factual belief [FB_{ij}] is represented as [FS_{ij}, CW_{ij}]. Where [FS_{ij}] represents a statement about the relative performance of a CET [i] on a particular attribute [j]. The [CW_{ij}] represents the confidence weight that belongs to a particular statement about the relative performance of a CET [i] on a given attribute [j]. Agent's hold seven factual beliefs for each CET [i]; one for each tech attribute [j] (see Equation #2). An agent's factual beliefs regarding a CET's attribute performance levels is labelled [$AttPerf_{FactualBelief}^{TechID}$].

$$\begin{bmatrix} AttPerf^{PV}_{FactualBelief} \\ AttPerf^{EV}_{FactualBelief} \\ AttPerf^{HP}_{FactualBelief} \end{bmatrix} = \begin{bmatrix} FB_{11} & \cdots & FB_{17} \\ FB_{21} & \cdots & FB_{27} \\ FB_{31} & \cdots & FB_{37} \end{bmatrix} = \begin{bmatrix} [FS_{11}, CW_{11}] & \cdots & [FS_{17}, CW_{17}] \\ [FS_{21}, CW_{21}] & \cdots & [FS_{27}, CW_{27}] \\ [FS_{31}, CW_{21}] & \cdots & [FS_{37}, CW_{37}] \end{bmatrix} \quad (2)$$

The quality of an agent's knowledge with regards to the performance of a particular CET is labelled [$Awareness_{TechID}$] and is represented by the closeness, or resemblance, of its [$AttPerf_{FactualStatement}^{TechID}$] to the actual performance of a CET [$AttPerf_{Actual}^{TechID}$]. This resemblance is determined by computing the Euclidian Distance between an agent's [$AttPerf_{FactualStatement}^{TechID}$] and a CET's [$AttPerf_{Actual}^{TechID}$] (see Equation #3).

$$\begin{aligned} X &= AttPerf_{FactualStatement} \\ Y &= AttPerf_{Actual} \\ Awareness_i &= \sqrt{\sum_{j=1}^{7}(X_{ij} - Y_{ij})^2} \end{aligned} \quad (3)$$

The actual state of an agent's knowledge, however, may not correspond to the agent's experienced confidence in the knowledge it holds. That is to say, despite (large) differences between an agent's [$AttPerf_{FactualStatement}^{TechID}$] and a CET's [$AttPerf_{Actual}^{TechID}$], the agent may experience, to varying degrees, confident regarding the quality of its knowledge base. Hence, the inclusion of confidence weights implies a distinction between what an agent *actually knows* and what it *believes* it knows.

An agent's confidence weights may range from 0 to 1, where 0 represents extreme uncertainty and 1 represents an absolute certainty with regards to some factual statement. Confidence weights are affected by the degree of discrepancy between incoming factual information and the agent's factual understanding of reality at that specific moment in time. When the discrepancy is large, confidence tends to diminish; when it is small, confidence will increase. Furthermore, an agent's confidence weights affect how strongly factual beliefs are affected by incoming information. Specifically, a high confidence weight tied to a particular [FS_{ij}], dampens the responsiveness of that [FS_{ij}] to incoming (discrepant) information. Section 3.4 describes in further detail how agent's update their factual beliefs (i.e. learn) about the performance of various CETs.

3.2.4 *Factual Belief System Model: Calibration*

The ECBCS model presents three settings with regards to the initial calibration of factual statements (see Table 15 & Table 16), and two settings with regards to confidence weights (see Table 15). Hence, there exist a total of 6 initial settings for initializing agents' factual belief systems. By default, factual statements (setting #2) and confidence weights (setting #1) are both initialized randomly.

Table 15. *Initialization Settings for Factual Statements.*

Setting	Name	Description
1	Zero	Agents start the simulation believing that all CETs perform *lower* on all attributes than their mainstream counterparts. Thus, the attribute performance lists for all agents are set to {0,0,0,0,0,0,0}.
2	Random	Agents start the simulation with randomly assigned factual statements. That is, the attribute performance lists for all agents

		are initialized as $\{X_1,X_2,X_3,X_4,X_5,X_6,X_7\}$, where X_i is a decimal number drawn from a uniform distribution with a lower bound of 0 and an upper bound of 1.
3	Perfect Knowledge	Agents start the simulation with perfect knowledge of each CETs performance on all attributes. Agents' subjective attribute performance lists are the same as the performance lists that each respective CET holds.

Throughout the simulation, agents learn about CETs and this affects their attitudes towards them. Hence, the initialization settings for agent factual belief settings impact the attitude formation process. Random default initialization seems justified since any other setting presumes that agents hold a pre-informed view of CET performances at the beginning of the simulation, which biases the learning process.

Table 16. *Initialization Settings for Confidence Weights.*

Setting	Name	Description
1	Random	Agents start the simulation with confidence weights that are randomly drawn from a uniform distribution with a lower bound of 0 and an upper bound of 1.
2	Maximal	Agents start the simulation with confidence weights that are set at their maximum value (0.95).

3.2.5 *Attitude Model: Operationalization*

Within the ECBCS model, every agent holds an attitude for each CET that summarizes the agent's evaluation of that CET in terms of a degree of (dis)favour. Attitudes are formalized as decimal numbers that range continuously from 0 to 1; where "0" represents a state of absolute disfavour and "1" a state of fervent favour (see Table 17).

Table 17. *Description of Attitude Levels and Related Evaluation Qualities.*

Attitude Level	Evaluation
0	Absolute disfavour
0.5	Moderate stance
1	Absolute favour

3.2.6 *Attitude Model: Formalization*

Figure 15 displays a visualization of how attitudes are computed within the ECBCS. The current section provides a detailed description of the computational procedures on which Figure 15 is based.

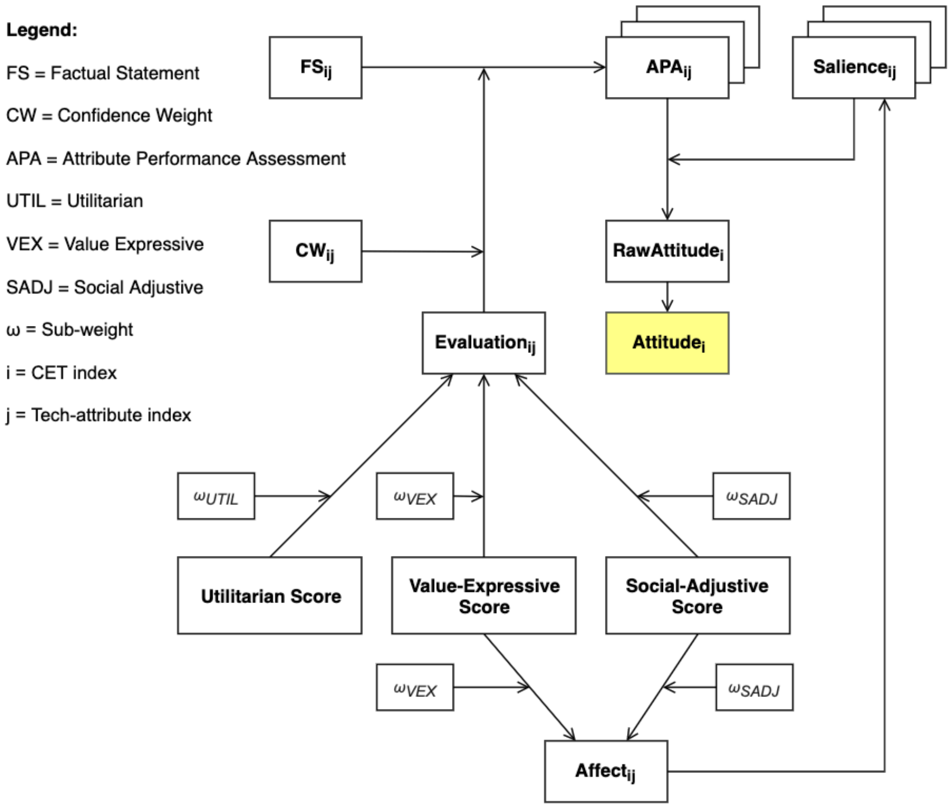


Figure 15. *Schematic Overview of Attitude Computation Procedure.*

A CET attitude is calculated as the weighted average of an agent's Attribute Performance Assessments (APAs) related to that CET (see Equation #4). An [APA_{ij}] summarizes: (1) what the agent beliefs is the performance of a CET [i] on attribute [j] (i.e. factual belief), and (2) what the agents thinks of that performance in evaluative terms (i.e. affective belief). Note that the output of Equation #4 is labelled as a '*RawAttitude*' score, this is because it is still one step removed from computation of the final 'Attitude' score. The *RawAttitude* for a given CET [i] is computed as the weighted mean of an agent's APAs for that CET, where the weights correspond to the salience levels tied to each APA.

$$RawAttitude_i = \frac{\sum_j^n salience_{ij} \cdot APA_{ij}}{\sum_j^n salience_{ij}} \tag{4}$$

A weight in Equation #4 is represented as the *salience* of an APA within the agent's mind at a given moment in time. As Fishbein and Ajzen (1975, p. 222) note "*a person's attitude is a function of his salient beliefs at a given point in time*". Salient beliefs are those that are especially active, or prominent when an agent engages in evaluative reasoning. The salience of a belief, or APA, is proportional to the influence it has on the formation of an agent's attitude with regards to a particular CET.

The salience of a given APA is presumed to be a function of the APA's affective content [$Affect_{APA}$]. The computation of APAs that serve one, or both, of the symbolic attitudinal function(s) is based on the agent's value system (see Table 5, Appendix 1). Values are affective beliefs, which means that APAs serving a symbolic function are also affectively-laden. The strength, or extremity of a value (i.e. the absolute difference of a value level from 0.5) is indicative of its affective intensity (see Equation #5). When an APA involves extreme values, an agent is presumed to experience an uncontrollable visceral and emotional reaction during evaluative reasoning. This autonomous physiological process is assumed to colour the agent's overall attitude regarding a particular CET (Critchley & Garfinkel, 2018). The affective content of an APA is represented as the sum of the strengths of each value [V] that is involved in the computation of that APA (see Equation #5).

$$ValueStrength_V = |ValueLevel_V - 0.5|$$

$$Affect_{APA} = \sum_{V}^{N_{Values}} ValueStrength_V \tag{5}$$

Salience is subsequently determined by exponentiating the affective content by parameter [π_8], which is set to 0.25 by default. The π_8 modulates the shape of the function; setting it at 0.25 (< 1) means the function holds a logarithmic shape. This implies that the effect of affective content on salience is strong at first, but diminishes as affective content increases (i.e. a diminishing slope). This function shape is based on the Weber-Fechner's law which states that *"the intensity of a sensation is proportional to the logarithm of the intensity of the stimulus causing it"* (Merriam-Webster, 2019b). In this case, emotional arousal represents the sensation, and thinking about a particular facet of CET performance serves as the stimulus. The [$Salience_{ij}$] variable is constrained to a range of 0.5 ≤ [$Salience_{ij}$] ≤ 1.

$$Salience_{APA} = Affect^{\pi_8}_{APA} \tag{6}$$

The computation of an [APA_{ij}] involves the factual belief of the relative performance of a CET [i] on a particular attribute [j] (i.e. [FS_{ij}]), a variable coined [$Evaluation_{ij}$] and one termed [$Certainty_{ij}$] (see Equation #7). Note that [APA_{ij}] is constrained to a range of [-1 ... 1]; where "-1" represents the most negative assessment and "1" the most positive.

$$APA_{ij} = FS_{ij} \cdot (Evaluation_{ij} \cdot Certainty_{ij}) \tag{7}$$

Before any computations are made, factual statements are mapped onto a scale ranging from -1 ≤ [FS_{ij}] ≤ 1. In doing so, 'lower' performance scores (< 0.5) become negative, and 'higher' (> 0.5) become positive (see Equation #8).

$$FS_{ij} = (FS_{ij} \cdot 2) - 1 \tag{8}$$

The [$Evaluation_{ij}$] variable multiplied by the [FS_{ij}] represents [APA_{ij}] under the condition that the confidence weight [CW_{ij}] for a CET's [j] performance level on attribute [i] equals 1. That is, if an agent is fully confident in its understanding of a CET's performance on a given attribute, then [APA_{ij}] equals [FS_{ij}] • [$Evaluation_{ij}$]. However, most of the time agents are not fully confident regarding the precision of their factual knowledge about the attribute performance levels of a given CET. For this reason, a variable coined [$Certainty_{ij}$] is included, which moderates the extent to which [$Evaluation_{ij}$] determines [APA_{ij}].

The computation of [$Certainty_{ij}$] is performed by exponentiating [CW_{ij}] by a function shape-parameter [π_7], which is set to 0.3 by default (see Equation #9). Exponentiating [CW_{ij}] by a value of lower than 1 results in a log-shape function. Theoretically, it is presumed that individuals tend to overestimate the quality of their knowledge (i.e. *the overconfidence effect*) (Dunning, Griffin, Milojkovic, & Ross, 1990). Hence, agent's subjective feeling of certainty increases swiftly as confidence increases from very low to medium levels. The sensitivity of [$Certainty_{ij}$] to changes in confidence, [CW_{ij}], diminishes as the latter reaches higher levels.

$$Certainty_{ij} = CW_{ij}^{\pi_7} \tag{9}$$

The calculation of [$Evaluation_{ij}$] involves multiplying so-called Attitude Function Domain Weights (AFD-Weights), represented as [$Func_k$, Att_j], with their respective sub-weights [ω_{ijk}], where [i] serves as a CET index, [j] as an attribute index and [k] as an attitude function index. For each technology attribute [j] there are three AFD-Weights; one for each attitudinal function [$Func_k$]. With regards to the utilitarian function [$Func_1$], the AFD-Weights and respective sub-weights are fixed. With regards to the symbolic functions [$Func_2$] and [$Func_3$], AFD-Weights and sub-weights are allowed to vary. The unfixed AFD-Weights are represented as [X_n], where [n] serves as an index. The AFD-Weights and corresponding sub-weights are depicted in the matrix depicted in Figure 6 (Appendix 2); sub-weights are depicted in curly brackets. Note that for each AFD-Weight there exist three sub-weights; one for each CET [i].

The [$Evaluation_{ij}$] variable is computed as the weighted average of AFD-Weights. Specifically, each AFD-Weight is multiplied by its respective sub-weight, after which they are summed. The outcome of the previous step is then divided by the sum of all sub-weights (see Equation #10).

Overview of indices used in Equation #10:

CET index [i] = {1,2,3} Tech attribute index [j] = {1,2,3,4,5,6,7} Attitude function domain index [k] = {1, 2, 3}

$$Evaluation_{ij} = \frac{\sum_k^N \omega_{ijk} \cdot [Func_k, Att_j]}{\sum_k^N \omega_{ijk}} \tag{10}$$

For instance, an agent's evaluation of the operating cost [j = 2] of a Heat Pump (not visible, not differentiated) [i = 3] is calculated as follows:

$$Evaluation_{32} = \frac{(\omega_{321} \cdot [Func_1, Att_2]) + (\omega_{322} \cdot [Func_2, Att_2]) + (\omega_{323} \cdot [Func_3, Att_2])}{(\omega_{321} + \omega_{322} + \omega_{323})} \tag{11}$$

Which translates into:

$$Evaluation_{32} = \frac{(1 \cdot -1) + (0 \cdot 0) + (0 \cdot 0)}{(1 + 0 + 0)} = -1 \tag{12}$$

As noted, an agent evaluates each tech-attribute [j] for a given CET [i] by multiplying its [FS_{ij}] with [$Evaluation_{ij}$] (see Equation #11). In order to determine an agent's [APA_{32}], we need to plug in the value of -1 into Equation #13 (for the sake of simplicity, a value of 1 is used for the [$Certainty_{32}$] variable). Plugging in a value of 0.25 into [FS_{32}], which is subsequently transformed into a value of -0.5 (see Equation #8), provides an APA of 0.5; which represents a positive assessment. This makes sense seeing that an FS of 0.25 represents, in this example, a 'lower' operating cost.

$$APA_{32} = -0.5 \cdot (-1 \cdot 1) = 0.5 \tag{13}$$

Note that the unfixed AFD-Weights [X_n] are computed on the basis of an agent's value system at a specific point in time. This implies that, although any given set of agents may be equally knowledgeable about the performance of a CET, they may hold quite different attitudes due to the fact that their value systems are dissimilar. For example, an agents that neither values power nor achievement will negatively assess the relatively high performance of a (visible and differentiated) CET in terms of purchasing cost. However, an agent that *does* value power and/or achievement will provide a more positive evaluation in the same situation. This is because the latter agent may feel that a highly-priced (visible, differentiated) CET allows him/her to gain social recognition through the display of affluence.

It is important to note that the AFD-Weights of the social-adjustive function are not activated in case a CET is not visible. For instance, a Heat Pump [i = 3] is not visible, nor highly differentiated, which means that the sub-weights linked to [X_6] and [X_7] are set to zero (see sub-weights [ω_{313}] and [ω_{353}]). When a CET is visible but not highly differentiated (as in the case of photovoltaics [i = 1]), the AFD-Weights [X_6] and [X_7] start to contribute to the computation of [$Evaluation_{ij}$] as their sub-weights are set to 0.5 (see sub-weights [ω_{113}] and [ω_{153}]). Lastly, when a CET is visible and highly-differentiated (as in the case of electric vehicles [i = 2]), the contribution of [X_6] and [X_7] is set to 1 (see sub-weights [ω_{213}] and [ω_{253}]).

The final step in the attitude formation process is the computation of an agent's overall attitude with regards to a particular CET [$Attitude_i$], where [i] serves as a CET index. The computation of [$Attitude_i$] transforms the [$RawAttitude_i$] score (see Equation #14) so that it falls within a range of 0 ≤ [$Attitude_i$] ≤ 1 using a sigmoid function (see Equation #14). A sigmoid function is applied in order to be able to vary the extent to which the attitude formation process may be sensitive to polarization. The parameter that modulates the slope (steepness) of the sigmoid curve is labelled [π_9], and is set to 10 by default. The higher the value of π_9, the steeper the curve, the stronger the polarization of agent attitudes. Values of π_9 approaching 0 will flatten out the curve and make attitudes converge on 0.5, which represents a moderate stance.

$$\begin{aligned} \lambda &= (-1 \cdot RawAttitude_i) \cdot \pi_9 \\ Attitude_i &= \frac{1}{1+e^{\lambda}} \end{aligned} \tag{14}$$

3.3 Media Exposure Model

The 'activate-media-exposure' procedure serves to model the exposure of agents to various kinds of media reports. Throughout the simulation, agents may be exposed to either 'expert', 'niche' or 'mass' media channels. Media can influence an agent's value system by altering what it believes is important/valuable in life (i.e. 'hot' influencing). Media can also influence an agent by altering what it believes it knows about the state of the reality (i.e. 'cold' influencing).

The influence of media on an agent's factual belief system is coined [*cold_media_dependence*] and is set to 1. Cold (factual) media has no functional alternative within the current version of the ECBCS model. A logical extension of the ECBCS model would be to include the possibility to simulate agent's First Hand Experiences (FHEs). Such FHEs would have to represent the process by which agents obtain factual information through direct interaction with and/or manipulation of reality; which, in the context of the current study, translates into the personal use of a CET.

The influence of media on an agent's affective belief system is coined [*hot_media_dependence*] and is computed as follows for every tick:

$$HotMediaDependence = ExperiencedUncertainty - (SocialLinks \cdot 0.01) \quad (15)$$

Where 'social links' represent the number of social ties an agents holds and experienced uncertainty is determined by the agent's perception of chaos or instability in its environment. It is presumed that the more socially connected an agent is, the less it depends on media for obtaining opinionated information (Jackob, 2010). Moreover it is presumed that the more uncertain agents are, the stronger they depend on information obtained from media to shape their viewpoints.

The computation of [*experienced_uncertainty*] involves multiple steps which are described in pseudo-NetLogo coding form in CodeViewer #1.

CodeViewer 1. *Steps Involved in the Computation of Experienced Uncertainty.*

```
1.   set environmental_weight = universalism
2.   set economic_weight = security
3.   set social_weight = (benevolence + security +
     conformity_tradition) / 3
4.   set sum_of_weights = (social_weight +
     environmental_weight + economic_weight)
5.   set system_instability =
     ((environmental_instability * environmental_weight) +
     (social_instability * social_weight) +
     (economic_instability * economic_weight)) /
     sum_of_weights
6.   set bias = mean_world_syndrome * 0.05
7.   set perceived_instability = system_instability * (1 +
     bias)
8.   set openness_to_experience = (universalism +
     self_direction + stimulation) / 3
9.   set openness = 0.5 * openness_to_experience
10.  set experienced_uncertainty = perceived_instability –
     openness
```

For a detailed overview of what each variable in the model represents see the Variable Overview in Appendix 3.

The [*system_instability*] variable is computed as the weighted average of the [*environmental_instability*], [*social_instability*] and [*economic_instability*] global variables (step 5, CodeViewer #1). Environmental instability is considered a stronger threat in the eyes of agents with high levels of universalism (step 1, CodeViewer #1), economic instability is assumed to threaten agents who value (economic) security (step 2, CodeViewer #1) and social instability is presumed to incite fear in the minds of agents that value benevolence, (social) security and conformity & tradition (step 3, CodeViewer #1).

As can be seen in step 6 of CodeViewer #1, the instability perceived by a given agent is represented as:

$$PerceivedInstability = SystemInstability \cdot (1 + (MWS \cdot 0.05))$$

$$MWS = \frac{(Exposure_{Mass} + Exposure_{Niche})}{Exposure_{Expert}} \tag{16}$$

MWS is an abbreviation of Mean World Syndrome. The exposure variables (i.e. $Exposure_{MediaType}$) simply count the number of times an agent is exposed to either mass, niche or expert media. It is presumed that agents that are exposed relatively more often to hot media will hold a higher level of MWS (see Equation #16). Agents with higher levels of MWS are inclined to perceive relatively higher levels of threat within their respective environments.

Agents that score high on the 'Openness To Experience' (OTE) personality trait are presumed to hold higher tolerance levels with regards to novelty and/or change. They are generally less risk averse than people who score lower on this particular trait (Roccas et al., 2002). Hence, high-OTE agents are predisposed to hold relatively lower levels of experienced uncertainty, and are therefore expected to exhibit lower levels of (hot) media dependence (see line 10 in CodeViewer #1).

A distinction is made between 'intentional' versus 'incidental' media exposure. In case of incidental exposure, agent's exert no control over the type and content of the media report they are exposed to; hence, if 'incidental' media exposure is activated the media type and content are selected randomly.

On the other hand, if intentional exposure is activated, then the selection of media type and content are based on an agent's personality traits and value system. Specifically it is presumed that agents with high levels of need-for-cognition are generally motivated to seek out factual information from expert media channels. Moreover, non-conformists and conspiracy-thinkers hold a proclivity to choose niche media over expert and mainstream channels. Lastly, conservative agents (i.e. those that value security, conformity, tradition and benevolence) are presumed to prefer mainstream (mass) media channels as these agents are theorized to be inclined to exhibit herd-like (mainstream-oriented) behaviour. Specifically, conservative agents will tend to select the media channels that cater to the needs of the majority of the population. Note that as agents attain higher levels of uncertainty, their tendency to select mass media increases. CodeViewer #2 shows the steps involved in the selection of media type.

CodeViewer 2. *Selection of Media Type.*

```
1.   if media_exposure = "intentional"
2.   then set media_types = ["expert" "niche" "mass"]
3.   then set weight_expert = need_for_cognition
4.   then set weight_niche = (non_conformism +
     conspiracy_thinking) / 2
5.   then set uncertainty = -0.5 + experienced_uncertainty
6.   then set weight_mass = ((security +
     conformity_tradition +
7.   benevolence) / 3) * (1 + uncertainty)
8.   then set weights = (list weight_expert weight_niche
     weight_mass)
```

Make a list that holds lists of paired media types and respective weights, like so:
[["expert", *weight_expert*] ["niche", *weight_niche*] ["mass", *weight_mass*]]

```
9.   then set pairs = (map list media_types weights)
```

For each list in [*pairs*], set [*media_type*] as the first item of a pair selected using the second item (i.e. "last i") as the weight. In doing so, media types with (relatively) larger weights are more likely to be selected.

```
10.  then set media_type first rnd:weighted-one-of-list
     pairs [ [i] -> last i ]
```

Note: the 'rnd:weighted-one-of-list' reporter works with the 'rnd' NetLogo extension, see link: https://ccl.northwestern.edu/netlogo/docs/rnd.html

The Equations #17, #18 and #19 show how the need-for-cognition, non-conformism and conspiracy-thinking (i.e. expert mistrust) traits are computed during each tick. Note that the index [j] represents Agent ID.

Non-conformism is presumed to be the weighted average of self-direction, stimulation and achievement. Values classified as progressive and self-regarding are presumed to induce non-conformism (see Figure 2, Schwartz, 2012, p. 13). The current computation of non-conformism is further substantiated by the notion that independence is motivated by self-direction and achievement values (Bardi & Schwartz, 2003). It is presumed that self-direction is the strongest driver of non-conformism followed by stimulation and achievement. The weights in Equation #17 are $\omega_1 = 3$, $\omega_2 = 2$, $\omega_3 = 1$.

$$NonConformism_j = \frac{\omega_1 SD_j + \omega_2 STM_j + \omega_3 ACH_j}{\sum_{i=1}^{3} \omega_i} \quad (17)$$

Need-for-cognition (NFC) represents a trait that reflects the extent to which agents are inclined towards enjoying effortful cognitive activities. It is presumed that this trait is (highly) prevalent within agent's who value universalism, self-direction and achievement (see e.g. Cacioppo et al., 1996; Sagiv & Schwartz, 2004). It is presumed that universalism and self-direction form the strongest determinants of an agent's need-for-cognition.

$$NFC_j = \frac{\omega_1 UNI_j + \omega_2 SD_j + \omega_3 ACH_j}{\sum_{i=1}^{3} \omega_i} \quad (18)$$

Conspiracy thinking [CT] represents an agent's propensity to mistrust the information provided by governments, universities, and other forms of (mainstream) expert entities (Heins, 2007). It is argued that sensation-seeking individualism can nurture an attitude of political cynicism, which increases the likelihood of engaging in conspiracy thinking. This sensationalistic individualism is presumed to be indicated by high levels of stimulation (excitement and sensation seeking), power and achievement (individualism). A sigmoid function is used to compute conspiracy thinking because it is presumed that 'moderate' or 'neutral' levels of expert mistrust are not realistic or common. In other words, agents tend to either trust or mistrust experts, not both. The shape parameters 5 [π_5] and 6 [π_6] allow one to experiment with different types of sigmoid functions (see Table 14 in Appendix 1 for an overview and description of shape parameters). The π_5 shifts the sigmoid curve down or up the x-axis. The π_6 modulates the steepness (slope) of the curve; the higher the values of π_6, the higher the contrast between those who trust versus those who tend to mistrust experts. By default, the parameters in Equation #19 are set to $\omega_1 = 3$, $\omega_2 = 2$, $\omega_3 = 1$, $\pi_5 = 0.5$, $\pi_6 = 15$.

$$X_j = \frac{\omega_1 STM_j + \omega_2 POW_j + \omega_3 ACH_j}{\sum_{i=1}^{3} \omega_i}$$

$$\lambda = -\pi_6 \cdot (X_j \cdot \pi_5) \tag{19}$$

$$CT_j = \frac{1}{1 + e^{\lambda}}$$

The content of media reports within the ECBCS model broadly fall into three categories: (1) random, (2) conservative or (3) liberal. If an agent is exposed to expert media, the content is generated randomly. This implies that there is currently no representation of agents selectively targeting pieces of factual information within the ECBCS model.

On the other hand, if an agent is (intentionally) exposed to niche or mass media, then it is allowed to exert agency over the content to which it is exposed. Agents are presumed to prefer exposure to congenial media content (i.e. selective exposure). Thus, liberal agents prefer exposure to liberal media, whereas conservative agents prefer exposure to conservative media.

CodeViewer 3. *Selection of Hot Media Content.*

```
set liberalism = (universalism + benevolence) / 2
set conservatism = (conformity_tradition + security +
(0.5 * power)) / 2.5
if liberalism ≥ conservatism then set media_content =
"liberal"
if liberalism ≤ conservatism then set media_content  =
"conservative"
if media_exposure = "incidental" then set
media_content = "random"
```

Intentional media exposure involves an agent's selective (i.e. deliberate) exposure to a particular media type and content. If societal threat drops below a certain threshold, mass media tends to report on subjects that positively affect liberal values and/or negatively affect conservative values:

```
if media_exposure = "intentional" &
if media_type = "mass" &
if societal_threat_level ≤ mass_media_bias
then set media_content = "liberal"
```

If societal threat exceeds a certain threshold, mass media tends to report on subjects that positively affect conservative values and/or negatively affect liberal values:

```
if media_exposure = "intentional" &
if media_type = "mass" &
if societal_threat_level ≥ (1 - mass_media_bias)
then set media_content = "conservative"
```

An agent can sometimes be exposed to mass media and perceive content that influences its value system in an arbitrary way:

```
if random-float 1 ≤ random_exposure then set
media_content = "random"
```

An agent can at times be exposed to alternative (niche) media and perceive content that influences its value system in an arbitrary way. However, it is presumed that niche media is generally more biased than mass media. That is, agent exposure to congenial content is presumed to be highest in case of niche media (see description of filter bubble phenomenon in *"Media Exposure"*, Section 2.3.5.6):

```
15.  if media_type = "niche" & if random-float 1 ≥
     filter_bubble then set media_content = "random"
```

The computation of [*liberalism*] (see line #1) and [*conservatism*] (see line #2) is based on Piurko, Schwartz & Davidov (2011).

When a majority of people within a society feels threatened by events taking place in their perceived environments, the emergence of certain epistemic, ideological and existential motives is expected to occur. The occurrence of these motives tend to favour conservative values as should become clear in the paragraphs below.

When people feel threatened they generally seek to reduce uncertainty, ambiguity and complexity by resorting to what they know and are familiar with: i.e. the status quo (Feygina, Jost, & Goldsmith, 2010). This *status quo bias* is characteristic of conservative values, which tend to value stability and order. It is presumed that the epistemic need to maintain a sense of certainty and stability becomes more salient as system instability increases.

Furthermore, threatened people are inclined to engage in tribalism as the affiliation with similar and/or familiar others may provide them with feelings of safety and reassurance (i.e. safety in numbers). Additionally, individuals may resort to the adherence of ideological viewpoints that are based on in-group dominance in order to increase their subjective perceptions of power, control and security in the face of threat. These existential and ideological motives are characteristic of conservative values, which generally emphasize loyalty and respect to one's in-group (Graham, Haidt, & Nosek, 2009).

Based on these postulations, it is assumed that in times of systemic instability and societal threat, mass media channels tend to report on conservative themes as these reflect the dominant sentiments present within a society during such times (see step 10-13 in CodeViewer #3). On the other hand, in times of peace, prosperity and stability, people may start to cherish more progressive and liberal views. Hence, in such times of low systemic instability, mass media are presumably more likely to report on liberal themes (see step 6-9 in CodeViewer #3).

The level of societal threat that exists within the agent population at given moment in time is represented simply as the average [*perceived_threat*] of all agents (see step 3, CodeViewer #4). Note that agents that value stimulation may perceive instability as something exciting. These agents will therefore hold relatively lower levels of perceived threat during times of systemic instability (see step 1-2, CodeViewer #4).

CodeViewer 4. *Computation of Societal Threat Level.*

Agents that value stimulation exhibit a relatively lower aversion to system instability:

```
1.   set excitement = 0.5 * stimulation
2.   set perceived_threat = perceived_instability –
     excitement
```

Societal threat level is computed as the average [*perceived_threat*] of all agents:

```
3.   set societal_threat_level = mean [perceived_threat] of
     agents
```

3.4 Cold Information Processing Model

Throughout the simulation, agents perceive cold (factual) information within their environments and adjust their belief systems accordingly. The current version of the ECBCS model includes the ability to simulate the following information sources: (i) factual (expert) media reports and (ii) word-of-mouth (factual) social interaction.

The ECBCS model also includes the possibility of adding a third option, namely first-hand experiences. A first-hand experience refers to an agent's direct (i.e. unmediated) experience with the world. An example, relevant to the scope of this study, is an agent experiencing what it is like to actually use a particular CET. It is presumed that hearing or reading about the use of a particular CET is a different experience than that of personally using that CET. For instance, actually experiencing how it is to drive an EV, or to generate your very own electricity using PVs, may affect one's belief system in ways that media exposure and/or social interaction cannot. However, the ECBCS model currently does not support such behavioural features. That is, the ECBCS model does not include a sub-model of how an agent's behaviour influences its beliefs and vice versa. the inclusion of such behavioural features forms a logical extension of the ECBCS model.

The following rules dictate how agents learn about the relative performance of the three CETs on the seven attributes included in the ECBCS model:

1. An agentset is selected at random from the population. The agentset is subsequently exposed to media reports. The size of the agentset (as a proportion of the total population) is set by [*media_exposure_rate*].

2. Select the type of media (i.e. "expert", "niche" or "mass") that a particular agent [X] from the agentset is exposed to.

    2.1. If exposure is "intentional", then the type of media exposure is selected based on agent's personality traits and value system configuration (see CodeViewer #3).
    2.2. If exposure is "incidental", then the type of media exposure is selected randomly.

3. If type of media exposure is "expert", then agent X engages in cold (or factual) information processing. The **cold-information-processing** procedure works as follows:

    3.1. Randomly target a CET [i].
    3.2. Randomly target a tech-attribute [j].
    3.3. Register the *a priori* (t0) attribute performance level [FS_{ij}^{t0}] that Agent X holds. Note that *a priori* (t0) refers here to 'before media exposure', whereas *a posteriori* (t1) refers to 'after media exposure'.
    3.4. Register the agent's *a priori* confidence weight corresponding to the selected CET attribute performance level [CW_{ij}^{t0}].
    3.5. Register the attribute performance (AttPerf) level that the CET holds (i.e. [*Actual_AttPerf_Level*]).
    3.6. Agent X perceives a slightly distorted version of [*Actual_AttPerf_Level*] (for computation steps see the pseudo-Netlogo code depicted in CodeViewer #5). The [*information_intake_distortion*] is introduced because it is presumed that agents are bounded in their ability to accurately process the factual information they receive (see Figure 14). Moreover, it is presumed that media reports may not be able to report

on the exact and absolute truth with regards to a CET's actual AttPerf level due to limitations inherent to conducting research.

CodeViewer 5. *Computation of Observed AttPerf Level.*

```
1.  set information_intake_distortion = abs (random-normal
    information_intake_error information_intake_error / 2)
2.  set price = position "purchasing cost" tech_attributes
3.  set increase_distortion = 1.5
4.  if att_index ≠ price then set
    information_intake_distortion =
    information_intake_distortion * increase_distortion
5.  set observed_attperf_level = actual_attperf_level +
    (information_intake_distortion - 2 * random-float
    information_intake_distortion)
```

Note: it is presumed that learning about the purchasing cost [j = 1] of a given CET is easier than obtaining knowledge about the other attributes. Hence, the range of potential information intake distortion is increased for attributes other than purchasing cost. Note also that [*observed_attperf_level*] is constrained to $0 \leq x \leq 1$.

3.7. An agent may be surprised by the information it receives. It is presumed that an agent's surprise level is exponentially proportional to the absolute difference between the *observed* AttPerf level and the agent's *expected* AttPerf level (see Equation #20). The [π_1] parameter determines the value of surprise where $X = 1$ (i.e. where the discrepancy between the expected and observed AttPerf levels is at its maximum). The [π_2] parameter modulates the shape of the function, where higher values of π_2 render the responsiveness of surprise to changes in X more precipitous (i.e. the surprise level's ascent towards π_1 becomes more sudden and steeper). Theoretically, it is presumed that the feeling of 'being surprised' constitutes a sudden and brief sensation (analogous to incurring an electric shock). Equation #20 is designed to model this characteristic (see Figure 1 in Nutter & Esker, 2006, p. 202); by default, $\pi_1 = 5$, $\pi_2 = 3$.

$$X = |AttPerf_{Observed} - AttPerf_{Expected}|$$

$$SurpriseLevel = \pi_1 \cdot X^{\pi_2} \tag{20}$$

3.8. Determine whether the surprise level of Agent X exceeds the prespecified [*surprise_threshold*]. If the level of surprise exceeds the [*surprise_threshold*], it means that the expected AttPerf level is significantly different from the one observed. This violation of the agent's expectation decreases the agent's certainty [CW_{ij}] with regards to the veracity of its presupposed *a priori* AttPerf level [FS_{ij}^{t0}]. As a consequence, the agent's [CW_{ij}] decreases (proportional to the difference between [*surprise_level*] and [*surprise_threshold*]). Vice versa, if the level of surprise falls below the critical threshold, an agent becomes more certain of the veracity of [FS_{ij}^{t0}] (see Equation #21).

$$X = SurpriseLevel - SurpriseThreshold$$

$$|X| = SurpriseExtremity \tag{21}$$

$$\begin{cases} \text{if } X > 0 \, then \, CW_{ij}^{t1} = \frac{CW_{ij}^{t0}}{1+SurpriseExtremity} \\ \text{if } X < 0 \, then \, CW_{ij}^{t1} = CW_{ij}^{t0} \cdot (1 + SurpriseExtremity) \end{cases}$$

3.9. Compute Agent X's [*Convergence_{Media}*] level. The [$Convergence_{Media}$] is the degree to which an agent updates its [FS_{ij}^{t0}] in congruence with the information it receives from a given media report. It is presumed that [$Convergence_{Media}$] is dependent on an agent's [CW_{ij}^{t1}] and [*cold_media_dependency*]. Uncertainty is presumed to have a stronger effect on [$Convergence_{Media}$] than [*cold_media_dependency*]; i.e. $\omega_1 = 2$, $\omega_2 = 1$.

$$Uncertainty = 1 - CW_{ij}^{t1} \tag{22}$$

$$Convergence_{Media} = \frac{(\omega_1 \cdot Uncertainty) + (\omega_2 \cdot ColdMediaDependency)}{\omega_1 + \omega_2}$$

3.10. Determine the updated (*a posteriori*) AttPerf level [FS_{ij}^{t1}] within the factual belief system of Agent X.

$$X = AttPerf_{Observed} - AttPerf_{Expected}$$

$$FS_{ij}^{t1} = FS_{ij}^{t0} + (Convergence_{Media} \cdot X) \tag{23}$$

$$0 \leq FS_{ij}^{t1} \leq AttPerf_{Observed}$$

3.11. If the surprise level of Agent X exceeds [*surprise_threshold*], then activate the **share-factual-information** procedure (see step 4). If this is not the case? Then the procedure ends.

4. If Agent X is surprised? Then select one of its peers [Y] to share the information with. Agent X is labelled as the 'sender', Agent Y as the 'receiver'. The following steps describe how information may spread through a social network through a process of Word-Of-Mouth (WOM) communication:

4.1. Agent Y receives information from Agent X regarding the performance level of a particular attribute [j] of CET [i]; i.e. the [FS_{ij}^{t1}] of Agent X. Agent Y subsequently processes this information by engaging in cold-information-processing (see step 3). Note that the [FS_{ij}^{t1}] of Agent X, which is communicated to Agent Y, substitutes the [*Actual_Attperf_Level*] variable in the equations reported throughout step 3.

4.2. Moreover, Agent Y calculates a different version of the 'convergence' variable, namely [$Converge_{WOM}$]. The [$Converge_{WOM}$] variable involves a [*Trust*] and a [$SocialStatus_{Sender}$] variable. The [*Trust*] variable represents the strength of the link (relationship) between a sender and a receiver. The [*SocialStatus$_{Sender}$*] variable holds the [*social_status*] of the sender, which is formalized as the sender's [*n_social_links*] multiplied by the global variable [*social_status_persuasiveness*]. It is presumed that uncertainty has strongest effect on [*Converge$_{WOM}$*] followed by trust and social status of the sender (which is assumed to be indicative of the sender's persuasiveness; see Equation #24); i.e. $\omega_1 = 1$, $\omega_2 = 0.5$, $\omega_3 = 0.25$.

$$\lambda_1 = \omega_1 \cdot (1 - CW_{ij})$$
$$\lambda_2 = \omega_2 \cdot Trust$$
$$\lambda_3 = \omega_3 \cdot SocialStatus_{Sender}$$
$$Convergence_{WOM} = \frac{\sum_{i=1}^{3} \lambda_i}{\sum_{i=1}^{3} \omega_i} \tag{24}$$

4.3. If Agent Y is surprised by the information it receives from Agent X, then Agent Y will subsequently share that information with one of its peers [Z]. Agent Y will then be labelled as the 'sender', and Agent Z as the 'receiver'. The information spreads through a social network as long as receiver agents are surprised by the information they obtain from sender agents. If a receiver agent is not surprised by incoming information, it will not share the information which puts a stop to the WOM process.

3.5 Hot Information Processing Model

Being exposed to an opinionated media report changes (to varying degrees) the content of an agent's value system. It is presumed that, over time, repeated exposure to certain opiniated media reports may have a notable impact on what an agent believes to be important/valuable in life. In the current ECBCS model, media generally influences an agent by pushing it towards a liberal or a conservative worldview. Hot media content is presumed to be strongly opiniated (attention-grabbing and sensationalistic) and constructed to persuade. Thus, it is presumed that hot media content tends to polarize an agent's value system.

The following steps are involved in the hot information processing procedure:

1. Determine whether media content is "random", "liberal" or "conservative".

2. Select a value from the agent's value system that is to be targeted by a media report:

   2.1. If content is "random" AND [*cultural_bias?*] is activated, then pick a value from the agent's value system based on the *cultural extremities* of the 9x BVT value types. Cultural extremity refers here to the deviation of a value type's *cultural mean* from the neutrality position (0.5). This means that the more extreme a value's cultural mean, the more likely it is to form the topic of discussion during opinionated media reports. For a computation of the cultural mean see Equation #33.

   2.2. If content is "random" AND [*cultural_bias?*] is NOT activated, then pick a value from the agent's value system at random by applying a uniform sampling probability of value type indices.

2.3. If content is not "random" (i.e. if it is "liberal" or "conservative"), then randomly pick a value from a prespecified selection of liberal and conservative (i.e. political) values.

3. Determine the importance level of the value that is communicated by the media report [$Value_{Media}$]:

   3.1. If perceived media content is "random" AND [*cultural_bias?*] is activated, then the communicated importance level is dependent upon its 'cultural valence'. If the cultural mean of a value falls above (below) the neutrality position then its cultural valence is positive (negative). If the valence is positive, then ascribe a high importance to [$Value_{Media}$]. If the valence is negative, then ascribe a low importance to [$Value_{Media}$].
   3.2. If perceived media content is "random" AND [*cultural_bias?*] is NOT activated, then ascribe a high or a low importance to [$Value_{Media}$] on a 50/50 basis.
   3.3. If perceived media content is "liberal", and if the value selected in step 2.3 is classified as liberal? Then ascribe a *very* high importance to [$Value_{Media}$]. If value selected in step 2.2 is classified as conservative? Then ascribe *very* low importance to [$Value_{Media}$]. Emphasis is placed on the adjectives here as the liberal and conservative biases are presumed to be more potent than cultural bias. Specifically, the value importance levels communicated by media are more extreme when liberal or conservative biases are active than when the cultural bias is activated. This presumption is based on the conviction that liberal and conservative biases are fuelled by ideological tribalism, whereas culture is less so
   3.4. If perceived media content is "conservative", and if value selected in step 2.2 is classified as conservative? Then ascribe a *very* high importance to [$Value_{Media}$]. If value selected in step 2.3 is classified as liberal? Then ascribe a *very* low importance to [$Value_{Media}$].

4. Determine the extremity of the agent's value level that is targeted by the media report [$Value_{Agent}^{t0}$]. Extremity is represented as the absolute difference of the agent's value level from the neutrality position (0.5). It is theorized that the more extreme a value, the more likely it is to serve a central role within an agent's self-conception (i.e. ego-involvement). Values central to the self-concept are more resistant to change.

5. Compute the agent's updated value level [$Value_{Agent}^{t1}$] according to Equation #25. Use [$Value_{Agent}^{t1}$] to replace the value with the corresponding index, i.e. [$Value_{Agent}^{t0}$], within the agent's value system. This puts an end to the hot information processing procedure.

$$\Delta Values = Value_{Media} - Value_{Agent}^{t0}$$

$$EgoInvolvement = \left|Value_{Agent}^{t0} - 0.5\right|$$

$$Convergence = (\Delta Values \cdot HotMediaDependence) \cdot (1 - EgoInvolvement) \tag{25}$$

$$Value_{Agent}^{t1} = Value_{Agent}^{t0} + (Convergence \cdot \boldsymbol{MediaInfluence})$$

3.6 Introspection Model

The introspection procedure allows agents to become aware of the configuration of their values systems (i.e. the relative ranking they ascribe to their values) and potentially change it as to increase its logical consistency. An agent may do so in two distinct ways: either through (1) *antagonistic* or through (2) *mutualistic* restructuring (see Table 18 for a description).

Table 18. *Description of Antagonistic and Mutualistic Restructuring of Value Systems.*

Type of Restructuring	Description
Antagonistic restructuring	It is illogical for agents to simultaneously cherish values that are in conflict with one another (i.e. antagonistic values). In case a set of conflicting values (e.g. power and benevolence) hold similar importance levels, the agent can solve for this dissonance by increasing or decreasing the level of a particular value relative to its antagonist.
Mutualistic restructuring	It is logically consistent for agents to cherish values that are complementary (or mutualistic) to one another. In case mutualistic values (e.g. achievement and power) hold dissimilar levels, the agent may solve this by moving the value levels closer towards one another.

Technological change presumably forms an important driver of this introspective process. New technologies may disrupt an agent's practical routines, which leads an agent to experience a heightened salience of conflicting normativities and moralities embedded in those routines (Swierstra, 2015). In doing so, technological disruption forces an agent to reflect on its value system, which is hypothesized to activate (to varying degrees) the processes of antagonistic or mutualistic restructuring.

The introspection procedure works as follows:

1. Randomly select a subset of the agent population that is potentially exposed to technological disruption during a given tick. Use the [*tech_disruption_scope*] global variable to control the size of the targeted agentset as a proportion of the total population.

2. For each agent in the selected agentset, determine whether it engages in introspection as a result of technological disruption. It is presumed that not all agents will experience a contemplative experience due to technological disruption. The global [*technological_change*] modulates the strength of this filter. The higher the degree (i.e. intensity) of technological change the more likely an agent will engage in introspection as a result of technological disruption.

3. If an agent engages in introspection, it has an equal chance (50%) of engaging in antagonistic versus mutualistic restructuring.

4. If an agent engages in antagonistic restructuring then the **execute-value-disruption** procedure is activated which works as follows:

    4.1. Pick random value(s) from agent value system that is (are) to be disrupted. It is presumed that any number of values can be disrupted during an instance of introspection. Append the indices of these values to a list called [*disrupted_value_indices*].

4.2. Determine the magnitude of potential value disruption. The maximum disruption level is set by the [*value_disruption_intensity*] global variable (see step 4.4).
4.3. For every item in [*disrupted_value_indices*], use that item (as an index) to obtain the importance levels corresponding to the agent values that are to be affected by the technology-induced disruption.
4.4. For each selected agent value level, i.e. [*value_levels_t0*], add or subtract a random float (X) with a range of LB ≤ X ≤ UB and append it to a new list called [*value_levels_t1*]. The LB (Lower Bound) is set to -1 • [*value_disruption_intensity*] and the UB (Upper Bound) is set as [*value_disruption_intensity*].
4.5. Update the agent's value system by replacing the disrupted values with [*value_levels_t1*].
4.6. The agent checks what value(s) is (are) affected by technological disruption. It subsequently engages in antagonistic restructuring of its value system. Specifically, if a value level increases (decreases) due to being disrupted, then its antagonist will decrease (increase) proportionately. Table 19 provides an overview of antagonist values. Each pair of antagonistic values finds itself on opposite sides of the circular BVT framework (see Figure 3 in Appendix 2).

Table 19. *Overview of Antagonistic Value Pairs.*

Antagonistic Value Pairs		
Stimulation	vs	Security
Self-direction	vs	Conformity & Tradition
Hedonism	vs	Universalism
Benevolence	vs	Power

5. If an agent engages in mutualistic restructuring then the following rules apply:

5.1. Randomly select a pair of mutualistic values. Table 6 (Appendix 1) gives an overview of mutualistic value pairs and a description of how their complementarity manifests itself.
5.2. Once a pair is selected, check which of the two is most extreme and/or least extreme. Note that extremity is computed by taking the absolute deviance of a value's level from the neutral point on the importance scale (0.5).
5.3. The least extreme value [X] subsequently moves its level *towards* the most extreme value [Y]. By doing so, mutualistic values beget similar importance levels. The global variable [*value_mutualism*] determines the strength of convergence between two mutualistic values.

3.7 Social Network Topology Model

The settings of the social network sub-model determine how agents, after being spawned, link up with one another to form a particular type of social network. There are two global parameters that change the topology of the network: (1) number of peer links each agent makes [*peer_group_links*] and (2) proportion of agents that makes a random link with another agent in the population [*random_links*]. By default [*peer_group_links*] is set to 5 and [*random_links*] to 0.1; these default settings are decided upon by means of a visual inspection of the type of social network topologies they generate. The desired network topology is based on the principle of *preferential attachment* and should exhibit a realistic combination of weak ties, social clusters, and wide bridges (Centola, 2015). Preferential attachment refers to the fact that any given node in the network is incentivized to link up with other nodes that exhibit similar characteristics. Figure 8 in Appendix 2 shows some exemplary topologies generated by the ECBCS (applying a fixed seed for the sake of reproducibility).

The following steps are undertaken to build the social network:

1. Ask each agent to look for [N] other agents that hold similar value systems and make a social link with them. The [N] other agents is set by [*peer_group_links*]. The similarity of value systems is computed as the Euclidian Distance between a targeted pair of agent value systems (see Equation #26); i.e. between Agent [X] and Agent [Y].

$$SocialDistance_{X,Y} = \sqrt{\sum_{i=1}^{N_{Values}} (X_i - Y_i)^2} \tag{26}$$

2. Ask each agent to randomly look for [N] other agents and make a social tie with them. The [N] other agents is set by [*random_links*].

3. Due to the stochastic nature of this procedure, it can occur that sometimes there exists an agent that has not been linked with any other agent after steps 1 and 2. Identify such agents and tell them to link up with a randomly selected agent from the population.

4. Once the social network is built, ask the agents to register the number of social ties they made as [*n_social_links*] and set their [*social_status*] as [*n_social_links*] • [*social_status_persuasiveness*]. It is presumed that the more social ties an agent holds, the higher its popularity and social status becomes.

3.8 Social Influence Model

The ECBCS model includes four Social Influence Model (SIM) settings that dictate how, during each interaction round, agents may interact with and influence each other's value systems.

Within the ECBCS model, agent face-to-face interaction happens primarily in dyads. That is, agents generally engage in *one-to-one* social influence process. Section 3.10 describes two forms of *many-to-one* social influence processes that are also included in the ECBCS model, albeit in a less sophisticated form than the *one-to-one* process described in the current section.

Each agent may, during a given tick, be confronted with the espoused values of another agent. When this happens, both agents first decide whether to interact or ignore one another. Only when both agents decide to interact are they able to exert an influence on each other's value systems.

All agents come equipped with three personal *interaction thresholds*, which determine an agent's proclivity to interact with other agents. In doing so, the interaction thresholds impose boundaries on the degree of (dis)agreement between two agents that is needed before they may influence one another. The inclusion of such thresholds is based on the workings of traditional 'bounded confidence' models of social influence (see e.g. Lorenz, 2007) and on more state-of-the-art versions of such models (see e.g. Jager & Amblard, 2005).

The thresholds also dictate the *interaction tactics* implemented by a pair of interacting agents. An interaction tactic refers to an agent's decision to either *individualize*, *assimilate* or *repulse* during an interaction. When an agent engages in what is referred to as *individualization*, it aims to move away (slightly) from the viewpoint of an agent that is considered highly similar to itself. The purpose of the assimilation tactic is to increase the similarity of one's viewpoint to the one expressed by an interaction partner. Lastly, the repulsion tactic focusses on increasing the dissimilarity of one's viewpoint with regards to the one communicated by an interaction partner.

The first interaction threshold is labelled the 'tolerance threshold' and represents an agent's level of leniency with respect to divergent viewpoints (see [ii] in Figure 16). When an agent's tolerance threshold is low, it is quick to disregard dissimilar viewpoints. Note here that 'to disregard' means 'to ignore'. The second threshold is labelled the 'polarization threshold' and represents an agent's hostility towards (highly) divergent perspectives (see [iii] in Figure 16). When an agents polarity threshold is low, it is quick to react in hostile ways to a dissimilar viewpoint. A hostile reaction is represented by an agent's decision to pursue a repulsion tactic during social interaction. Lastly, an agent's individuation threshold (see [i] in Figure 16) determines the level of value (dis)similarity at which an agent decides to implement the individualization tactic.

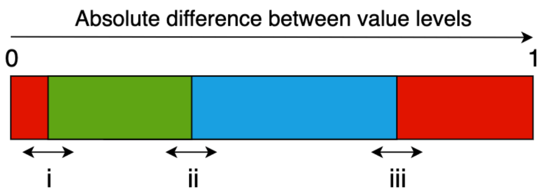


Figure 16. *Visualization of Interaction Thresholds and Related Interaction Outcomes.*

As can be seen in CodeViewer #6, an agent's interaction thresholds are determined by their personality traits. These personality trait levels are calculated on the basis of the agent's value system. Hence, within the ECBCS model, an agent's interaction behaviour is contingent upon the configuration of its value system during a given interaction round.

CodeViewer 6. *Computation of Personality Traits and Interaction Thresholds.*

Openness to experience relates positively to tolerance of divergent perspectives. Links between personality traits and values are based on Roccas et al (2002).

```
1.    set openness_to_experience = (universalism +
      self_direction + stimulation) / 3
```

Narrow mindedness relates positively to intolerance of divergent perspectives (i.e. hostility).

```
2.    set narrow_mindedness = (security +
      conformity_tradition + (1 - benevolence)) / 3
```

Extroversion relates to tendency to approach / interact with people.

```
3.    set extroversion = (stimulation + achievement + (0.5 *
      hedonism)) / 2.5
```

Introversion relates to tendency to avoid / not interact with people.

```
4.    set introversion = (conformity_tradition + (0.5 *
      security)) / 1.5
```

Set base-level of confidence threshold using the global variable [*tolerance*]. Set base-level of polarity threshold using the global variable [*hostility*]. Set base-level of individuality threshold using the global variables [*individualism*].

The global variable [*interaction_threshold_heterogeneity*] modulates the strength of the effect that certain traits have on the level of the interaction thresholds.

```
5.    set tolerance_threshold = (tolerance + ((extroversion
      - introversion) *
      interaction_threshold_heterogeneity))

6.    set polarity_threshold = ((1 – hostility) +
      ((openness_to_experience - narrow_mindedness) *
      interaction_threshold_heterogeneity))
```

It is presumed that agents with high levels of self-direction tend to behave more individualistic.

```
7.    set individuality individualism + (self_direction *
      random-float 0.1)
```

Note: tolerance thresholds have a range of 0 ≤ x ≤ 0.5, and polarity thresholds are constrained to a range of 0.5 ≤ x ≤ 1.

Table 20. *Overview* of *Social Interaction & Influence Model Settings.*

ID	SIM Setting	Description	Interaction Variables
1	Assimilation	In assimilation mode, agents will *always* interact as their value dissimilarity always exceeds the polarity threshold and never surpasses the confidence threshold. Moreover, agents will always decide to use the converge tactic. Lastly, ω_1 is fixed and will therefore have no variable effect on the level of value convergence.	ω_1 TT_1 PT_1
2	Biased assimilation	In biased assimilation mode, agents with a value dissimilarity that surpasses the confidence threshold will inevitably fall below the polarity threshold. This means that agents stop interacting with one another if their value dissimilarity exceeds their combined confidence thresholds. Moreover, ω_2 weakens as value dissimilarity increases. This means that more similar agents will exhibit a stronger converge (i.e. similarity bias).	ω_2 TT_2 PT_2
3	Biased assimilation and repulsion	Agents with a value dissimilarity that surpasses the combined confidence threshold and that falls below the joint polarity threshold will ignore each other (i.e. not interact). The ω_3 turns *negative* as value dissimilarity increases past a critical threshold of 0.5. A negative influence weight leads to a repulsive force between any pair of interacting agents; that is, they move away from one another in terms of value levels (their value systems become more dissimilar).	ω_3 TT_3 PT_3
4	Biased assimilation, repulsion and optimal distinctiveness*	This setting functions much like setting 3. The only difference is that ω_4 will make agents with a very low level of value dissimilarity repel one another. In other words, highly similar agents will move away from each other in terms of value levels.	ω_4 TT_4 PT_4

ω_i = Influence Weight, with [i] as SIM setting index.
TT_i = Tolerance Threshold, with [i] as SIM setting index.
PT_i = Polarity Threshold, with [i] as SIM setting index.
* = the default SIM setting.

Equation #27 describes the variables shown in Table 20. Note that for setting #4, a special kind of influence weight becomes activated when [*value_dissimilarity*] < [*individuality*]. The multiplication of Ω with $-\lambda$ results in a strong *negative* influence weight when agent values are highly similar to one another. The strength of the repelling force that becomes active when agent values show strong resemblance is modulated by the shape parameter π_2. By default, π_2 is set to 25.

$$
\begin{aligned}
&\text{Value Dissimilarity} = X = \left|Value_{AA}^{t0} - Value_{PA}^{t0}\right| \\
&\text{Standard Influence Weight} = \Omega = 1 - (2 \cdot X) \\
&\omega_1 = 1 \\
&\omega_1, \omega_2, \omega_3 = \Omega \\
&\text{Optimal Distinctiveness} = \lambda = {\pi_2}^{-\pi_2 \cdot X} \\
&\omega_4 = \begin{cases} \text{if } (X < Individuality) \text{ then } \omega_4 = \Omega \cdot -\lambda \\ \text{if } (X > Individuality) \text{ then } \omega_4 = \Omega \end{cases} \\
&TT_1 = 1 \\
&TT_2, TT_3, TT_4 = \frac{TT_{ActiveAgent} + TT_{PassiveAgent}}{2} \\
&PT_1 = 0 \\
&PT_2 = 1 \\
&PT_3, PT_4 = \frac{PT_{ActiveAgent} + PT_{PassiveAgent}}{2}
\end{aligned} \tag{27}
$$

The following steps are involved in the execution of the social interaction & influence sub-model:

1. Ask agents to update their interaction threshold variables. CodeViewer #6 shows how the interaction threshold variables are updated for every tick.

2. Ask a subset of agents from the population to choose an interaction partner from within their personal social network (i.e. from the agentset that it is linked with). The agent that actively calls for an interaction is labelled the *Active Agent* (AA), whereas the agent that (passively) receives the AA's call for an interaction is labelled the *Passive Agent* (PA).

3. If the agents choose to interact with one another, select the value type that forms the topic of discussion. By default, the selection of a value type tends to favour the most extreme values within the AA's value system. This is because agents are inclined to proselytize strongly held values. The ECBCS model also includes the possibility to randomize the selection of a value type.

4. Register the importance level of the value type selected in step 3 for the AA [$Value_{AA}^{to}$] and for the PA [$Value_{PA}^{to}$]. Subsequently, determine the (absolute) difference between [$Value_{AA}^{to}$] and [$Value_{PA}^{to}$] and save the outcome to variable [*value_dissimilarity*].

5. Add some random error (noise) to the agents' assessment of one another's value levels. This serves to crudely represent the bounded knowledgeability of agents with regards to figuring out *exactly* how strong an interaction partner values something. The global variable [*value_assessment_error*] modulates the potential magnitude of the error in the perceived (dis)similarity of [$Value_{AA}^{to}$] and [$Value_{PA}^{to}$].

6. Load the influence weights and agent interaction thresholds based on the type of SIM setting (see Table 20) that is activated.

7. Determine whether (i) [*value_dissimilarity*] is smaller than the confidence threshold or whether (ii) [*value_dissimilarity*] is larger than the polarity threshold. If (i) is true, then the interaction outcome may be to assimilate or

to individualize. If (i) is true and [*value_dissimilarity*] is also smaller than the individuality threshold, then the standard influence weight Ω is multiplied by −λ; which means agents will engage in individualization. If (ii) is true then agents will engage in repulsion.

8. Select influence weight based on the selected SIM setting. The influence weight determines the direction, and (partly) the strength of value level convergence (or divergence).

9. Compute the magnitude of value change for $Agent_{AA}$ and $Agent_{PA}$ (i.e. $\Delta Value_{AA}$ and $\Delta Value_{PA}$) using Equations #28 and #29. The global variable [*value_convergence*] is set to 0.25 by default and has a range of 0 ≤ [*value_convergence*] ≤ 0.5. $Convergence_{Agent}$ is proportionally related to the following variables: the SIM setting influence weight, *ValueConvergence*, $SocialInfluence_{Agent}$; that is, if any of these variables increase (decrease) in magnitude, $Convergence_{Agent}$ will also. The $EgoInvolvement_{Agent}$ variable is inversely related to $Convergence_{Agent}$.

10. Determine the post-interaction (updated) value importance levels of AA and PA (i.e. $Value_{AA}^{t1}$ and $Value_{PA}^{t1}$) and use these levels to replace the level of $Value^{t0}$ within the value systems of the respective interactants.

$$
\begin{aligned}
&SocialInfluence_{Agent} = [0.5 \leq SocialStatus_{Agent} \leq 1.5] \\
&EgoInvolvement_{Agent} = |Value_{Agent}^{t0} - 0.5| \\
&Convergence_{AA} = \omega_i \cdot \boldsymbol{ValueConvergence} \cdot SocialInfluence_{PA} \cdot (1 - EgoInvolvement_{AA}) \\
&Convergence_{PA} = \omega_i \cdot \boldsymbol{ValueConvergence} \cdot SocialInfluence_{AA} \cdot (1 - EgoInvolvement_{PA})
\end{aligned}
\tag{28}
$$

$$
\begin{aligned}
&\Delta Value_{AA} = Convergence_{AA} \cdot (Value_{PA}^{t0} - Value_{AA}^{t0}) \\
&\Delta Value_{PA} = Convergence_{PA} \cdot (Value_{AA}^{t0} - Value_{PA}^{t0}) \\
&Value_{AA}^{t1} = Value_{AA}^{t0} + \Delta Value_{AA} \\
&Value_{PA}^{t1} = Value_{PA}^{t0} + \Delta Value_{PA}
\end{aligned}
\tag{29}
$$

11. Social ties are presumed to remain fixed throughout the simulation. However, they are weighted and these weights [ω_{Link}] may change over time. The weight of a social link [ω_{Link}] captures the trust that exists between a pair of agents. Based on the interaction outcome (i.e. assimilation versus repulsion), update the strength of the weight of the link between the two agents. Positive interaction (convergence) leads to an increase of trust, whereas a negative interaction outcome leads to a decrease in trust (see Equation #30). Trust is constrained to a range of 0 ≤ x ≤ 2.

$$
\begin{aligned}
&\mu\Delta Values = \frac{|\Delta Value_{AA}| + |\Delta Value_{PA}|}{2} \\
&Trust \begin{cases} \text{if "assimilation"? then } Trust = \omega_{Link} \cdot (1 + \mu\Delta Values) \\ \text{if "repulsion"? then } Trust = \omega_{Link} \cdot (1 - \mu\Delta Values) \end{cases}
\end{aligned}
\tag{30}
$$

3.9 Social Media Model

The Social Media Model (SMM) is embedded into the SIM procedure. Specifically, when the SMM is activated, an agent (under the condition that is an active user of social media) may discuss its values with any other agent that is also an active social media user. Social media relaxes to some degree the constraint of agents being allowed to communicate only with others who are proximate within the social network (see step 2 of the SIM Model description in Section 3.8). In other words, as long as two agents are active users of social media, they may communicate with, and potentially influence, one another.

The SMM forms an alternative to the interaction partner selection step of the SIM (step #2 of Section 3.8). The following steps apply to the SMM:

1. Check whether an agent is an active user of social media. If this is not the case? Then continue to step 2 of the SIM procedure.

2. Draw a random decimal (X) from a uniform distribution with range 0 to 1. If X falls below the level of global variable [*social_media_activity*], then tell the agent to select another agent from the population that has not yet been linked with and that holds an active social media status. If [*social_media_activity*] is set high, then active users of social media tend to interact with other agents through social-media channels. If [*social_media_activity*] is set low, then active users of social media tend to interact with others through non-social-media channels (e.g. face-to-face).

3. Check whether any potential interaction partners were identified in step 2; if this is not the case? Then pick an interaction partner from social links (i.e. resort to step 2 of the SIM).

4. After a potential interaction partner is selected continue with step 3 of the SIM procedure.

3.10 Multilateral Influence Model

The Multilateral Influence Model (MLIM) represents the pressure an agent experiences to conform to the views and expectations of its social reference group (also referred to as its peer group).

The dominant view of a peer group with regards to a particular BVT value type is computed as the weighted mean of the corresponding importance levels (i.e. viewpoints) that the group's members hold (see Equation #31). It is presumed that an agent feels a stronger need to assimilate with the views of trusted others. Hence, the peer value levels are weighted by the strength of the relationships (i.e. trust) of those peers with the agent under consideration. Note that [i] serves as an index for the number of peers [n] an agent holds.

$$\mu LocalMajority_{Agent} = \frac{\sum_{i=1}^{n}(PeerValue_i^{Agent} \cdot Trust_i^{Agent})}{\sum_{i=1}^{n} Trust_i^{Agent}} \quad (31)$$

It is presumed that conformism to a social reference group increases when an agent experiences feelings of uncertainty. This effect is represented as an increase in the $PeerPressureIntensity_{Agent}$ variable. The effect that experienced uncertainty has on $PeerPressureIntensity_{Agent}$ is moderated by the global variable [*peer_pressure*] (see

Equation #32). Moreover, agents characterized by high levels of non-conformism will experience less peer pressure. Lastly the magnitude of the difference in value levels between that of an agent and the agent's social reference group (formalized as Δ_{Agent}) has a positive effect on the peer pressure experienced by that agent (see Equation #32). The variable $MLIvalue_{Agent}^{t1}$ represents the post-interaction value level of a given agent when the MLIM is activated.

$$
\begin{aligned}
&PeerPressureIntensity_{Agent} = \boldsymbol{PeerPressure} \cdot (1 + ExperiencedUncertainty_{Agent}) \\
&\Delta_{Agent} = \mu LocalMajority_{Agent} - Value_{Agent}^{t1} \\
&PeerPressure_{Agent} = \Delta_{Agent} \cdot PeerPressureIntensity_{Agent} \cdot (1 - NonConformism_{Agent}) \\
&MLIvalue_{Agent}^{t1} = \begin{cases} \text{if } \Delta_{Agent} > 0 \text{ then } MLIvalue_{Agent}^{t1} = Value_{Agent}^{t1} + |PeerPressure_{Agent}| \\ \text{if } \Delta_{Agent} < 0 \text{ then } MLIvalue_{Agent}^{t1} = Value_{Agent}^{t1} - |PeerPressure_{Agent}| \end{cases}
\end{aligned}
\tag{32}
$$

3.11 Culturalization Model

The Culturalization Model (CM) represents the cultural conformity pressures that an agent may experience during a given round of interaction. Culturalization is represented as a force that pulls an agent's value levels towards their cultural standards. The cultural standard of a particular value is represented simply as the population mean of that value (i.e. $CulturalMean_i$). Note that N_{Agents} represents the number of agents that constitute the population (which is 500 by default). The index [i] represents one of the BVT value types, and [j] serves as an index for agent ID.

$$
CulturalMean_i = \frac{\sum_{j=1}^{N_{Agents}} ValueLevel_{ij}}{N_{Agents}} \tag{33}
$$

Note that an agent's assessment of the cultural mean for a given value is presumed to be imperfect (see *"Culturalization"*, 2.3.6.1). For this reason, a decimal number (X) is added or subtracted from the cultural mean calculated in Equation #33. The [X] is drawn from a uniform distribution with a range determined by the global variable [*cultural_expectation_error*]:

$$
\begin{aligned}
&LB = (-1 \cdot \boldsymbol{CulturalExpectationError}) \\
&UB = \boldsymbol{CulturalExpectationError} \\
&LB \leq CulturalMean_{Agent} \leq UB
\end{aligned}
\tag{34}
$$

The following steps describe how the CM is executed:

1. Compute the pre-interaction (t0) deviation of each agent with regards to the cultural mean.

2. Compute the post-interaction (t0) deviation of each agent with regards to the cultural mean.

3. Determine whether an agent moves away (t0 deviation < t1 deviation) or towards (t0 deviation > t1 deviation) cultural mean. If agent moves away from cultural mean, then the process of culturalization is activated.

4. Compute the culturalization effect. The computation of the culturalization effect contains three components ($\lambda_1, \lambda_2, \lambda_3$):

   4.1. The first component (λ_1) ensures that the strength of the culturalization effect is inversely proportional to the magnitude of an agent's cultural deviation (see Equation #35). Shape parameter 1 (π_1) enables one to experiment with different function shapes. The π_1 is set to 1 by default, which translates into a linear function. Setting $\pi_1 < 1$ results in a log-shaped function, which leads the culturalization to kick in quite rapidly and become gradually *less* sensitive to changes in an agent's cultural deviation as the latter increases in size. On the other hand, setting $\pi_1 > 1$ results in culturalization becoming gradually *more* sensitive to changes in an agent's cultural deviation as the latter increases in magnitude.
   4.2. The second component (λ_2) equates culturalization with the global variable [*culturalization_strength*], which is set to 1 by default. An agent's experienced uncertainty may boost the culturalization effect (see Equation #35).
   4.3. The third component (λ_3), warrants that the effect of culturalization decreases as an agent's level of non-conformism increases (see Equation #35).

$$CulturalDeviation^{t0}_{Agent} = Value^{t0}_{Agent} - CulturalMean$$

$$CulturalDeviation^{t1}_{Agent} = Value^{t1}_{Agent} - CulturalMean$$

$$\Delta Deviation_{Agent} = CulturalDeviation^{t0}_{Agent} - CulturalDeviation^{t1}_{Agent}$$

$$\lambda_1 = -1 \cdot |\Delta Deviation_{Agent}|^{\pi_1} \tag{35}$$

$$\lambda_2 = \boldsymbol{CulturalizationStrength} \cdot (1 + ExperiencedUncertainty_{Agent})$$

$$\lambda_3 = 1 - NonConformism_{Agent} \cdot \boldsymbol{NonConformismStrength}$$

$$Culturalization_{Agent} = \begin{cases} \text{if } \Delta Deviation_{Agent} > 0 \text{ then } Culturalization_{Agent} = 1 \\ \text{if } \Delta Deviation_{Agent} < 0 \text{ then } Culturalization_{Agent} = 1 + \prod_{i=1}^{3} \lambda_i \end{cases}$$

5. Determine the post-interaction (t1) value levels for interacting agents including the effect of culturalization, i.e. $CulturalizedValue_{Agent}^{t1}$ (see Equation #36). Update the agent systems accordingly.

$$\Delta Value^{Culturalized}_{Agent} = \Delta Value_{Agent} \cdot Culturalization_{Agent} \tag{36}$$

$$CulturalizedValue^{t1}_{Agent} = Value^{t0}_{Agent} + \Delta Value^{Culturalized}_{Agent}$$

3.12 Model Outcome Metrics

Table 10 (Appendix 1) provides an overview of variables that constitute the most important metrics of the current version of ECBCS model.

Values and CET attitudes are measured at the level of individual agents and may be analysed in several ways. For instance, the measurements of these metrics can be tracked over time (e.g. time-series design). Due to the fact that these metrics are measured at an agent-level, they generate a fairly large number of data points. Hence, visualizations of their development over time is preferably done using density plots or heat maps rather than line or scatter plots. The measurements of these metrics can also be statistically compared to one another, or with themselves, at one or across different discrete points in time (i.e. by means of a cross-sectional, repeated-measures, or mixed-design). Societal awareness, confidence, threat and uncertainty and CET sentiments are measured at the population level. Similar to the agent-level metrics, these population-level metrics are all suited for visualization and descriptive and/or statistical analysis.

Societal awareness indicates the general state of the knowledge of agent population with regards to the performance of each CET. As societal awareness increases, it indicates that a majority of agents within the population is becoming more accurately knowledgeable about the performance of each CET. Societal confidence indicates how confident agents generally are with regards to their knowledge bases.

Societal threat and uncertainty are important drivers of value change. When they are low, progressive and self-transcendent values tend to fare well, whereas high levels of threat and uncertainty increase the appeal of conservative and self-regarding values (see Chapter #2). It is interesting to see whether the ECBCS is able to reproduce these trends.

Lastly, CET sentiments are computed as indicators of the relative distribution of positive (versus negative) CET evaluations within the agent population. High (low) levels of a given CET sentiment variable indicate that a majority of agents within the population hold positive (negative) views regarding that CET.

4 Model Verification & Validation

The ECBCS is constructed with the aim of studying and characterizing the behaviour of the non-formal model of belief system change presented in Chapter #2. In other words, the ECBCS is built for theoretical exposition. The main objective of theoretical exposition is to obtain a comprehensive understanding of a model's behaviour (Edmonds et al., 2019). The biggest risk to reaching this objective is the presence of coding errors (i.e. *bugs*) (Edmonds et al., 2019). Mitigating this risk is done through model verification.

Model verification involves checking whether there are no significant disparities between what one *thinks* a model is doing and what it is *actually* doing (Galán et al., 2009). Hence, verification makes sure that the modeller "built the *thing right*". Validation, on the other hand, involves checking whether the modeller "built the *right thing*" (Calder et al., 2018; van Dam et al., 2013). Since the ECBCS is built for theory exposition, its quality should not be assessed in terms of how well its output fits with real-world data (Edmonds et al., 2019). Hence, the quality of the ECBCS is evaluated predominantly on the basis of the verification procedure.

Another risk to obtaining a sound understanding of model behaviour is the potential presence of modelling *artefacts*. A modelling artefact occurs when there is a mismatch between the set of assumptions that causes the occurrence of a certain phenomenon and the set of assumptions that the modeller believes is responsible for producing that phenomenon (Galán et al., 2009). It is useful, in this regard, to categorize the assumptions embedded within the ECBCS model as being either *core* or *accessory* assumptions. Core assumptions are those considered to constitute the purpose of the model. Ideally, core assumptions are the only ones present within the model (Galán et al., 2009). Accessory assumptions are, often arbitrarily, included within the ECBCS model in order for it to become a complete and functioning whole (Galán et al., 2009; Papadelis & Flamos, 2019). Such accessory assumptions are formulated on the basis of the modeller's intuitions and/or common practices within the social simulations field. They may also be imposed through the use of a particular modelling platform (i.e. NetLogo) (Galán et al., 2009). An additional distinction can be made between *significant* and *non-significant* assumptions, where the former refers to assumptions that form the cause of some significant modelling outcome (Galán et al., 2009). Table 21 summarizes the four assumption categories.

Table 21. *A Classification of Modelling Assumptions.*

	Non-significant	Significant
Accessory	Insignificant model feature	Artefact
Core	Hypothesis refuted	Hypothesis supported

As can be seen in Table 21, an artefact occurs when a set of accessory assumptions is considered to be non-significant by the modeller when it is, in fact, significant (Galán et al., 2009). The presence of artefacts would mean that the ECBCS is not representative of the conceptual model that it aims to study. This is because changing some accessory assumption(s) creates an alternative model that still includes all of the core assumptions, but that generates significantly different outcomes (Galán et al., 2009).

There are several techniques one may implement to hunt down artefacts (for a comprehensive overview, see e.g. Galán et al., 2009); one of which is to conduct a thorough exploration of the model's *behaviour space* by executing an Uncertainty Analysis (UA) in combination with a Sensitivity Analysis (SA). The term 'behaviour space' refers here to the collection of possible outcomes that the ECBCS is able to generate.

The UA-SA conducted as part of the current study aims to gauge the (in)significance of the assumptions embedded within the ECBCS model. The UA helps to systematically map out the behaviour space of the ECBCS (Edmonds et al., 2019). The SA enables one to assess the robustness of emergent properties to, and quantify the variability in modelling outcomes resulting from marginal changes in core and/or accessory assumptions (ten Broeke, van Voorn, & Ligtenberg, 2016). The SA also facilitates the selection and calibration of experimental parameter settings as it helps to identify, out of a large number of inputs, the most influential ones (Iooss & Saltelli, 2017).

4.1 Verification

Verification of the ECBCS model is executed by means of a series of *unit tests*. More specifically, individual units or components of the model are tested by providing them with well-defined inputs and assessing whether the consequent outputs are in agreement with the *a priori* expectations of the modeller. In other words, each component is tested to verify whether what it does is the same as what it should do. Note that, in order to ensure reproducibility, unit tests are performed with a fixed seed. Table 1 (Appendix 5.1) shows in what ways the model components may be tested. Table 2 (Appendix 5.1) presents an overview and description of the performed unit tests.

4.2 Uncertainty & Sensitivity Analysis

4.2.1 Global Sensitivity Analysis: Design & Implementation

The systematic evaluation of the ECBCS comprises of a quantification of (i) model output variability and (ii) of its sensitivity to model input parameters (henceforth referred to as *factors*) (Ligmann-Zielinska, Kramer, Spence Cheruvelil, & Soranno, 2014). The first part of the model evaluation is referred to as the Uncertainty Analysis (UA) and the second part as the Sensitivity Analysis (SA). The objective of the UA is to quantify the distribution of model outcomes given factor uncertainty (Ligmann-Zielinska et al., 2014). The goal of the SA is to evaluate how changes in factor settings contribute to model outcomes (Ligmann-Zielinska et al., 2014).

The technique implemented to reach these objectives is termed Global Sensitivity Analysis (GSA). The GSA procedure involves drawing a large number of random samples from the *factor space* and subsequently running a simulation for each distinct sample of factor settings (ten Broeke et al., 2016). The term 'factor space' refers to an abstract representation of the collection of settings (i.e. *input ranges*) that each distinct factor is allowed to take on (see "Sampling Range" in Table 11, Appendix 1).

The lower and upper bounds of the input range are defined as follows:

$$InputRange_{LowerBound} = NominalValue \cdot 0.5$$
$$InputRange_{UpperBound} = NominalValue \cdot 1.5 \tag{37}$$

Samples are drawn from the sampling range in a uniform manner as to avoid imposing unnecessary restrictions on the sampling of factor settings. The samples are drawn from the factor space using a statistical technique called Latin Hypercube Sampling (LHS). The reason for this is that LHS guarantees a uniform sampling of factor settings given a Y dimensional factor space constrained to a limit of X samples (van Dam et al., 2013).

The selection of factors included in the GSA is limited to the ones that are able to vary continuously. The discrete (categorical and Boolean-type) factors are all set to their default state during the GSA. The main reason for this is that many of the discrete factors alter the structural composition of the model; i.e. they constitute the on/off switches of various sub-models. Other discrete factors alter the way agents are calibrated during initialization or control the activation of simulation visualizations. The scope of the current GSA is limited to analysing the model's behaviour within the boundaries of this default model structure. All continuous factors (i.e. *sliders*) are included in the GSA since it is not known *a priori* how the outcomes of the ECBCS model responds to changes in their respective settings. The LHS procedure was carried out in R Studio (2019). The LHS samples are subsequently used to perform model runs with using NetLogo's BehaviorSpace (see Figure 17).

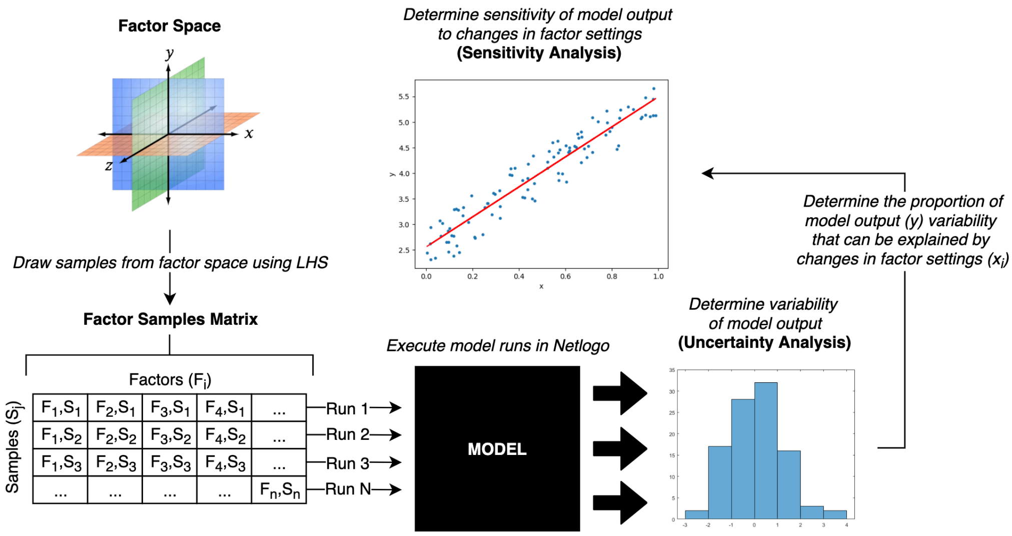


Figure 17. *Visual Overview of GSA Procedure.*

When running simulations one ought to be aware of the possible existence of so-called *nuisance factors* (Lorscheid, Heine, & Meyer, 2012). Nuisance factors are defined here as model inputs that are not classified as independent variables but that do affect model outcomes. Controllable nuisance factors, or *control variables*, are controlled for by fixing their settings during model experimentation. Uncontrollable nuisance factors, or *noise factors*, require a different approach. An example of such a noise factor is the application of the pseudorandom number generator during simulation runs. The pseudorandom number generator enables the execution of stochastic process elements, but it also induces variability in the distribution of model outcomes corresponding to simulation runs with identical factor settings. This undesirable variability is henceforth referred to as *experimental error*.

In order to assess whether there exist other noise factors apart from the pseudorandom number generator, the model is run twice with identical factor settings and with a fixed random seed. Since the outcomes are identical, it is concluded that the pseudorandom number generator constitutes the only noise factor in the current version of the ECBCS model.

One way to come to grips with the experimental error induced by the pseudorandom number generator is to estimate its impact on the variance of model outputs (Lorscheid et al., 2012). Declaring that 'a metric's experimental error is large' is the same as stating that the *variability in the variance* of a particular metric across identical simulation runs is high. Specifically, experimental error occurs when the spread (e.g. standard-deviation) of a metric behaves erratically vis-à-vis a measure of its centrality (e.g. arithmetic mean) across identical simulation runs. Hence, the higher a metric's experimental error, the higher the number of replicate simulations needed to obtain a *meaningful* estimation of the statistical distribution of a metric. An estimation is meaningful when it is not, or to a minimal extent, obfuscated by experimental error.

The behaviour of a metric's *coefficient of variation* (CV) across duplicate simulation runs provides a sound indication of the degree of experimental error that is involved in its computation (Lorscheid et al., 2012). The CV is computed as the ratio of a metric's standard-deviation (σ) to its arithmetic mean (μ) (see Equation #38).

$$CV_{metric} = \frac{\sigma_{metric}}{\mu_{metric}} \tag{38}$$

A metric's CV typically stabilizes as the number of replications increases, as dictated by the law of large numbers. The point at which increasing the number of replications does not drastically alter a metric's CV anymore can be used to gauge the number of runs (N) required for obtaining meaningful results (Lorscheid et al., 2012). The figures in Appendix 5.2 show that the CVs of the ECBCS model's metrics stabilize quite rapidly. This indicates that there is no need for executing a large number of replications during the GSA and/or during subsequent model experiments.

Table 18 (Appendix 1) provides an overview of experimental model settings. These model settings describe the design of the simulation runs during the GSA and experiments described in Chapter #5.

4.2.2 *Global Sensitivity Analysis: Results & Discussion*

4.2.2.1 *Uncertainty Analysis*

Appendix 4.1 show a compilation of visualizations that provide insight into the variability of model metrics over simulation runs with different factor settings. Note that the UA visualizations depict the cross-simulation variability in the arithmetic mean of model metrics. It is assumed that the arithmetic mean provides a sound indication of the most common (i.e. representative) measurement level for each metric during individual simulation runs. However, one must keep in mind that there exist situations wherein this assumption may be invalid, such as when the distribution of metric measurements is highly skewed (the median would then provide a better measure of centrality) or when a distribution is multi-modal. Lastly, a measure of dispersion (such as the standard-deviation) is not included in the results of the GSA as this information is not considered to be relevant for addressing the UA and SA objectives stated in the previous section.

Notwithstanding the potential shortcomings of the arithmetic mean as a centrality measure, it can be seen that POW, SEC, CT, BEN and UNI exhibit a relatively higher variability compared to the other metrics (see Appendix 4.1). This result can be explained by the way media biases are represented within the ECBCS. Specifically, these value types are affected more strongly by and/or are addressed more frequently during the activation of media exposure procedures.

With respect to the attitude and sentiment metrics, the uncertainty analysis points out that the those related to heat pumps exhibit a relatively larger density of data points towards the lower end of the measurement spectrum (see Appendix 4.1). This indicates that, within the boundary of the current model parameter sweep, agents tend to be less positive about heat pumps compared to EVs and/or PVs.

Note that due to skewness, sentiment levels are transformed using a $\log_{10}$ operation. Untransformed sentiment metrics range from a minimal value of $1/N_{Agents}$ to a maximum of $N_{Agents}/1$, where $N_{Agents} = 500$ by default. The transformed range for the sentiment metric measurements becomes MIN ≈ -2.69 and MAX ≈ 2.69.

4.2.2.2 *Sensitivity Analysis*

In the current GSA setup, the sensitivity of model outputs to factor manipulation is formalized as the proportion of model output variance explained by changes in the settings of a particular factor. Specifically, for each model metric a multiple Ordinary Least Square (OLS) regression function is applied which includes the factors described in Table 11 (see Appendix 1) as predictor variables. Standardized regression coefficients (β-coefficients) are used as indicators of the strength and direction of predictor effects. The higher the absolute value of a particular β (i.e. |β|) the higher a metric's sensitivity to changes in that predictor. The value of a β-coefficient represents the magnitude of change in a metric (expressed as z-scores, or number of standard-deviations) resulting from an increase in the value of a factor by one standard-deviation. Hence, β-coefficients are directly comparable to one another within the context of a single regression model. This enables one to quickly identify the most influential factors (i.e. the ones with the highest contribution to a model's coefficient of determination) with respect to a particular metric.

Appendix 4.3 provides visualizations of the β-coefficients (including a 95% confidence interval) of each factor included in the GSA for each of the 12x model metrics (nine value types and three attitudes). Note that, according to classic frequentist tradition, an effect is considered statistically significant if the zero-value lies outside the 95% confidence interval of a given β-coefficient.

Table 13 in Appendix 1 provides an overview and description of methods used to communicate the GSA results. The interested reader is referred to Appendix 4.2 and 4.3 for a visualization of GSA results.

4.3 Validation

Traditionally, models are validated by comparing their output with empirical data to see whether these are in accordance with one another (van Dam et al., 2013). Validation of the ECBCS model cannot be executed in this manner because it is built for theoretical exposition. Hence, the ECBCS is validated on the basis of *literature validation*. Literature validation involves checking whether model outcomes correspond to conclusions reached through theoretical research and/or non-ABM modelling efforts (van Dam et al., 2013).

Only processes that have been studied extensively using non-ABM approaches lend themselves for this type of validation. An example of such a process is the diffusion of information within a network of actors. Moreover, the dynamism of values generated by the ECBCS can be validated on the basis of extant literature.

4.3.1 Validation of Information Diffusion Dynamics

Information diffusion is defined here as the process by which ideas, opinions or beliefs, that are perceived as new, spread via communication channels over time amongst the members of a social system (Rogers, Medina, Rivera, & Wiley, 2005). Research points out that the spread of novel information in a social system tends to follow an S-shaped (i.e. sigmoid) trajectory (Rogers et al., 2005). As can be seen in Figure 1 (Appendix 5.3), the ECBCS generates such diffusion dynamics, which adds to its validity.

4.3.2 Validation of Value Dynamics

The following sections aim to validate the dynamics of values included in the ECBCS in light of the findings and/or postulations of existing research.

4.3.2.1 Validation: Value System Configuration

When activated repeatedly over the course of a simulation, the introspection process should lead to the emergence of logically consistent value systems. The logical consistency of value systems is described by the circular BVT value type framework as depicted in Figure 3 (Appendix 2).

Figure 2 (Appendix 5.3) shows a matrix with Pearson's correlation coefficients [ρ] in the upper-left part of the matrix and scatter plots depicted in the lower-right. Due to the large amount of data points crammed into the small-sized cells of the lower-right side of the matrix, a decision is made to use contours instead of scatter dots. Lastly, an OLS regression function is applied to each cell and visualized as a red line. The OLS regression helps to interpret the Pearson's correlation coefficient that describes the linear relationship between a pair of values. Specifically, the scatter plots and OLS regressions provide information with respect to the validity of the assumption of linearity involved in the computation of the Pearson's correlation coefficients.

Figure 2 (Appendix 5.3) shows that, when repeatedly activated, the introspection procedure does indeed lead to more logically consistent value system configurations. Across the diagonal of the matrix one observes the abbreviations of the 9x BVT value types and their respective statistical (frequency) distribution. Activating *only* the introspection procedure leads value types to, over time, adopt a bimodal distribution.

The non-diagonal cells of the matrix provide information on the bivariate distribution (i.e. association) of value level measurements between pairs of value types. For example, the association between universalism (UNI) and benevolence (BEN) can be described by ρ = 0.72, which communicates a strong positive relationship. When looking at the scatter plot one observes two high-density data-point clusters; one where the data-points hold low measurement levels for BEN and for UNI, and the other where data-points hold high measurement levels for both BEN and UNI. The nature of this bivariate distribution indicates a strong linear and positive relationship. This agrees with the BVT, which postulates that universalism and benevolence are complementary (mutualistic) values (Schwartz, 2012). On the other hand, benevolence (BEN) and power (POW) are negatively related ρ = -0.55, which is theoretically correct considering that the BVT describes them as an antagonistic pair of values (Schwartz, 2012). Thus, on the basis of Figure 2 (Appendix 5.3), one may tentatively draw the conclusion that the introspection algorithm generates a process that is theoretically valid, which adds to the overall validity of the ECBCS model.

4.3.2.2 *Validation: Emergence of Social Milieus*

Assessing whether the ECBCS is able to generate a valid representation of social milieus can be done by applying a statistical dimensionality-reduction procedure to the default model output. Specifically, a Principal Component Analysis (PCA) is executed on the data generated by the ECBCS to expose the higher-order structure of agent value systems.

Figure 7, 8 and 9 (Appendix 5.3) present the results of the PCA. Figure 8 (Appendix 5.3) projects each 12-dimensional (9x value + 3x attitudes = 12x metrics) data-point onto a 2D-plane. The coordinates that describe the position of each observation on the plane represent its factor loadings on the 2x principal components that, together, explain a majority of variation within the dataset.

Figure 9 (Appendix 5.3) helps to interpret the meaning of the dimensions that define the 2D-plane depicted in Figure 8 (Appendix 5.3). The first dimension (Dim1) represents a distinction between values classified as 'progressive' (left-side of the plot) and those labelled 'conservative' (right-side of the plot). Specifically, observations (i.e. agents) placed to the right of the 2D-plane (Figure 8, Appendix 5.3) tend to cherish progressive values, whereas agents placed towards the right of the plot ascribe a higher importance to conservation. The second dimension (Dim2) represents a distinction between self-transcendent (upper hemisphere of the plot) and self-enhancement values (lower hemisphere of the plot). Hence, agents placed towards the lower-end of the 2D-plane (Figure 8, Appendix 5.3) cherish values that are aimed at self-enhancement, whereas agents placed towards the upper-end of the plane ascribe a higher importance to self-transcendent values. This higher-order structure of agent value systems corresponds with the BVT value continuum (see Figure 3, Appendix 2) (Schwartz, 2012) and WIN-model (Vringer, Aalbers, & Blok, 2007, p. 555, fig. 1); which adds to the validity of the ECBCS model.

It is interesting to note that attitudes towards HPs and PVs are of a more progressive and self-transcendent nature than the one regarding EVs. This makes sense theoretically, since EVs are technologies that are evaluated more strongly in terms of the social-appraisal they may bestow on an owner. In doing so, EVs become vehicles for self-enhancement. Moreover, although EVs are considered to be progressive technologies, they arguably form an *incremental* rather than a radical innovation. That is, EVs constitute a product upgrade rather than a completely different mode of transportation. PVs and HPs, on the other hand, are more radically different from the mainstream technologies they aim to replace. That is, the use of PVs and HPs require that a user changes its entire private energy infrastructure, whereas the use of an EV resembles that of an ICEV (except for differences in the refuelling procedure). This may explain why HP and PV attitudes hold a more progressive position on the 2D-plot (Figure 8, Appendix 5.3).

4.3.2.3 *Validation: Sociodynamics of Values*

The social influence model (SIM) contains 4x settings, each of which can be validated on the basis of extant research. Validation of the SIM is done by running the ECBCS with *only* the SIM activated. The SIM variables are fixed at their default settings (see Variable Scheme in Appendix 3).

Figure 3 (Appendix 5.3) shows how agents choose to unconditionally assimilate the level of importance they ascribe to the 9x value types with that of an interaction partner. It can be observed that after approx. 1000 ticks, all of the agents converge on a neutral position for each of the 9x value types. This emergent phenomenon of consensus formation from initial dissimilarity has been observed in ample models of social influence processes (Flache et al., 2017).

The second SIM setting (i.e. biased assimilation) generates a value change process that can be observed in Figure 4 (Appendix 5.3). A notable difference from the value change process generated by the first setting is the emergence of distinct groups of agents that ascribe similar levels of importance to a particular value. This phenomenon corresponds to the observed existence of clusters, or segments, of people within a society that hold similar value systems (e.g. homophily*)*. The third SIM setting (biased assimilation and repulsion) produces similar dynamics as the second setting does, except that it seems to generate a stronger polarization in the distributions of value importance levels.

The fourth and final SIM setting initially generates dynamics similar to those of settings #2 and #3; this can be seen in the multimodal distribution of value levels during ticks ≤ 1000. However, as ticks progress beyond that point, agents begin to converge on the neutrality position as in the case of SIM setting #1. It looks as if the Optimal Distinctiveness (OD) mechanism eventually leads to a domination of assimilative over repulsive forces, which leads agent viewpoints to collapse into a state of consensus. See Figure 6 in Appendix 5.3 for a more detailed explanation of the observed pattern of belief change under setting #4. The author was not able to validate this phenomenon on the basis of existing literature.

5 Model Experiments & Reflection

The following sections describe the design and execution of the current model experiments. The structure of this chapter is loosely based on the Design of Experiments (DOE) framework presented by Lorscheid et al (2012, p. 30). The first section describes the experiments in terms of their respective objectives and a specification of experimental variables. The second section describes the data analysis performed with the output of each experiment. The third, and final section presents an interpretation and discussion of the results (to be found in Appendix 6.0 to 6.4).

5.1 Experimental Setup

The questions presented in Table 22 are used to construct the current experimental setup (see Table 18 in Appendix 1):

Table 22. *Overview of Experimental Questions.*

Experiment	Question
1	How do various SIM variable settings influence the development of values and attitudes within an agent population?
2	How does culturalization affect the development of values and attitudes within an agent population?
3	How do various forms of media exposure impact the development of values and attitudes within an agent population?
4	How does systemic instability affect the development of values and attitudes within an agent population?

Specifying the Independent Variables (IVs) for each experiment (i.e. the experimental parameterization) was done on the basis of the experiment's objective and the results of the GSA described in the previous section. Specifically, given the objective of an experiment, the most relevant and influential factors (see Appendix 4.3) were selected to be subjected to experimental manipulation. Factors shown to exert little or no influence are omitted from experimental manipulation.

The IVs are subjected to a discrete 2-level (low versus high) manipulation. In other words, two settings are specified for each IV; one which represents a low value for a particular IV and the other representing a high value. Hence, experiments take the form of A/B tests where A = *(model output | low IV setting)* and B = *(model output | high IV setting)*. The specification of low and high values for each IV (i.e. experimental calibration) is also done on the basis of the GSA results.

The current model experiments are characterized by a full-factorial design as this is considered to be the most straightforward way of performing an experimental parameter sweep (van Dam et al., 2013). This implies that each experimental run corresponds to a point in a space with N_{IV} dimensions and N_{Level} manipulations. Although full factorial designs are straightforward and conceptually easy to grasp, they require vast amounts of computational resources as N_{IV} and/or N_{Level} increase in size (van Dam et al., 2013). The decision for a 2-level instead of a X-level (where X > 2) manipulation is made for the sake of striking a balance between the amount of data needed to reach a conclusion with regards to the experimental objectives and the computational resources needed for running the model experiments.

5.2 Experimental Data Analysis

Table 17 (Appendix 1) provides an overview of the visualization and statistical modelling techniques implemented in order to draw conclusions with respect to the hypotheses formulated throughout Section 5.3.

5.3 Experimental Results

5.3.1 *Default Model Output: Descriptive Results*

Table 23 presents a collection of statistics that describes the distribution of measurements for each of the 12x (agent-level) model metrics. The statistics depicted in Table 23 are based on a cross-section of model output-data during the last (i.e. 2000th) tick. The figures in Appendix 6.0 visualize the development of agent-level model metrics under default model settings.

Table 23. *Descriptive Statistics Default Model Outcomes.*

VAR	N**	Mean	SD	Median	MIN	MAX	Range	Skew	Kurtosis
ACH	10000	0.25	0.09	0.24	0	0.7	0.7	1.12	2.68
BEN*	10000	0.58	0.31	0.8	0	0.96	0.96	-0.36	-1.67
CT	10000	0.62	0.22	0.52	0.25	1	0.75	0.2	-1.72
EVatt	10000	0.41	0.04	0.41	0.26	0.59	0.33	0.37	0.74
HED	10000	0.18	0.04	0.18	0	0.86	0.86	1.97	29.3
HPatt	10000	0.55	0.1	0.57	0.28	0.79	0.51	-0.37	-1.08
POW*	10000	0.48	0.32	0.36	0.04	1	0.95	0.17	-1.79
PVatt	10000	0.37	0.12	0.39	0.11	0.63	0.52	-0.21	-1.22
SEC*	10000	0.55	0.3	0.34	0.1	1	0.9	0.17	-1.88
SD	10000	0.4	0.19	0.44	0	0.77	0.77	-0.37	-1.09
STM	10000	0.29	0.11	0.29	0	0.61	0.6	-0.2	0.02
UNI*	10000	0.55	0.32	0.78	0	0.99	0.99	-0.29	-1.78

* = The large difference between the mean and median of these metrics is due to the bimodal nature of their distributions (see figures in Appendix 6.0).
** = 500 agents • 20 replications = 10,000 observations.

It is worth noting that the measurements of BEN, POW, SEC and UNI, over the course of a simulation run, bifurcate into a bimodal distribution under default model settings. This can be explained by the polarizing effect that media has on these values. BEN and UNI share a liberal character, whereas SEC and POW can be categorized as conservative (Piurko et al., 2011). Within the ECBCS, media tends to polarize a population along a 'liberal – conservative' continuum. Other value types, such as ACH, HED, SD and STM cannot be classified as being typically liberal or conservative. This explains why the agent population exhibits a higher degree of consensus formation with respect to these 'politically-neutral' value types.

5.3.2 *Experiment #1 : Social Interaction & Influence*

<u>Experimental Narrative & Hypotheses</u>

Energy consumers interact with each other over the course of 2000x interaction rounds. Each energy consumer is characterized by a unique value system and set of interaction thresholds. Energy consumers may (to varying degrees) be tolerant or hostile with respect to divergent perspectives. Energy consumers may also differentially experience the need to individualize. This experiment explores the emergent macro-level outcomes of manipulating the nature of the interaction & influence tactics operated by energy consumers.

Specifically, levels of (**A**) tolerance, (**B**) hostility, (**C**) individuation and (**D**) agent interaction threshold heterogeneity are manipulated. It is expected that set-up I = [*high* ***A****, low* ***B****, low* ***C****, low* ***D***] leads to a high degree of homogeneity in what people consider to be important or valuable in life. On the contrary, set-up II = [*low* ***A****, high* ***B****, low* ***C****, low* ***D***] should lead to a more polarized value landscape in which distinct clusters of like-minded agents emerge. Lastly, set-up III = [*low* ***A****, high* ***B****, high* ***C****, low* ***D***] is expected to generate a similar dynamic to II, however the clusters are expected to be less 'tight' (i.e. exhibit more within-group variability) due to the heightened need of agents to individualize. With regards to attitude dynamics, it is expected that I leads to an overall consensus of attitude levels, whereas II and III should generate more disagreement in the attitude levels of energy consumers.

This leads to the formulation of the following hypotheses:

H1.1 = The level of tolerance is inversely related to the variability of value levels within an agent population.

H1.2 = The level of hostility is proportionally related to the variability of value levels within an agent population.

H1.3 = The level of individuality is proportionally related to the variability of value levels within segments of an agent population.

The results of experiment #1 can be found in Appendix 6.1. Comparing the visualizations, one can observe that, for each value type, measurements exhibit a stronger tendency to convergence under setup I than setup II and III. This observation is substantiated by the fact that the standard-deviations for each value type under setup I are all relatively smaller than those computed under setup II and III (see Table 24). This observation supports both H1.1 and H1.2, which postulate that the overall variability of value measurements should be lower in I than in II.

Table 24. *Experiment #1: Standard-Deviations of Metric Measurements for Experimental Setup I, II and III.*

	σ_I	σ_{II}	σ_{III}	σ_{II}/σ_I	σ_{III}/σ_I
ACH	0.17	0.22	0.24	1.29	1.41
BEN	0.21	0.27	0.27	1.29	1.29
CT	0.17	0.23	0.24	1.35	1.41
HED	0.22	0.27	0.26	1.23	1.18
POW	0.22	0.27	0.27	1.23	1.23
SEC	0.12	0.19	0.21	1.58	1.75
SD	0.17	0.23	0.24	1.35	1.41
STM	0.15	0.20	0.21	1.33	1.40
UNI	0.22	0.27	0.26	1.23	1.18

σ_I = standard-deviations linked to setup #1.
σ_{II} = standard-deviations linked to setup #2.
σ_{III} = standard-deviations linked to setup #3.

Furthermore, comparing Figures 2 and 3 in Appendix 6.1, it seems that there exist more well-defined clusters of like-minded agents under setup II than under III. The value level measurements are more 'smeared out' under III. More technically, the distributions of value measurements in III generally show a less distinctive (visual) pattern of multimodality than those of II. This observation supports H1.3, which posits that the variability *within* clusters of like-minded agents should be greater under III compared to I and II.

5.3.3 *Experiment #2 : Culturalization*

<u>Experimental Narrative & Hypotheses</u>

During simulation runs, the value systems of energy consumers are affected by (sub-)cultural forces. Specifically, whenever agents contemplate the importance they ascribe to particular values, they take into account, and are influenced by the dominant views of a reference group.

On the highest level, culture encompasses the dominant views of an *entire* agent population. On a lower level, cultures – or more specifically: sub-cultures – represent the most common views of a *subset* of an agent population (i.e. a social group or segment). Cultures affect value systems by pulling an agent's value level closer towards the position that a majority of agents belonging to the same reference group subscribes to. It helps to conceive of culture as an entity endowed with agency. In doing so, one can state that the 'goal' of culture is to eliminate the differences in the value system configurations of agents belonging to a particular social group or population.

This experiment explores the proposed homogenizing effect of culture on agent value systems. This is done by manipulating the strengths of (**A**) global and (**B**) local culturalization. Variable **A** is represented by model parameter [*culturalization_strength*] and variable **B** by [*peer_pressure*]. Experimental setup I = [*low **A**, low **B***] serves to generate a baseline scenario for assessing the effects of **A** and **B** on the development of agent value levels. Experimental setup II = [*high **A**, low **B***] is expected to generate a convergence, or assimilation of value levels across an entire agent population. Experimental setup III = [*low **A**, high **B***] is expected to produce a segment-level convergence of value levels. In other words, II should lead to global consensus formation (i.e. reduce the spread of value levels at a population-level), whereas III should lead to more localized pockets of consensus formation (i.e. reduce the spread of value levels at a segment-level).

This leads to the formulation of the following hypotheses:

H2.1 = The strength of global culturalization is inversely proportional to population-level variance in value measurement.

H2.2 = The strength of local culturalization is inversely proportional to segment-level variance in value measurements.

The results of experiment #2 can be found in Appendix 6.2. The anticipated effects of [*culturalization_strength*] and [*peer_pressure*] on the population-level distribution of value measurements cannot be observed. Specifically, the visualisations linked to setup II (Figure 2, Appendix 6.2) and III (Figure 3, Appendix 6.2) do not differ in any noticeable way from that of setup I (Figure 1, Appendix 6.2). Hence, H2.1 and H2.2 are not supported.

5.3.4 *Experiment #3 : Media Exposure*

Experimental Narrative & Hypotheses

During simulation runs, energy consumers are exposed to media reports. Energy consumers tend to enjoy having their beliefs confirmed. Hence, they are inclined to pick out media channels that broadcast congenial viewpoints. Congenial viewpoints are those that harmonize with one's belief system. At other times, energy consumers may be exposed to media channels incidentally. When this happens, they are not able to exert control over the type of media reports they are exposed to, thereby increasing the likelihood of being exposed to divergent (non-congenial) perspectives. The type of media exposure (intentional versus incidental) that is activated during each instance of media exposure is stochastically determined by the variable (**A**) [*intentional_vs_incidental_exposure*]. Specifically, **A** represents (and modulates) the probability that an agent is intentionally exposed to media; i.e. *A = P(intentional | media exposure)*.

In order to operate, media businesses must obtain, and preserve, the attention of an audience. Attracting attention works by reporting on topics and viewpoints that spark a crowd's interest. Mass media must appeal to the interests of a large audience and is therefore incentivized to report on mainstream topics and viewpoints (i.e. cultural bias). Niche media, on the other hand, is less responsive to trends in mainstream viewpoints. Thus, agents consuming niche media are more likely to be exposed to culturally-defiant views. Besides being culturally biased, media may frame information in ways that advocate a liberal or conservative viewpoint. The variables (**B**) [*mass_media_bias*] and (**C**) [*filter_bubble*] modulate the strength of mass and niche media biases, respectively.

Media appeal to people's emotions to trigger and retain interest. Media do so by exploiting people's salience and negativity biases. Specifically, media frame information in a way that engages listeners through provoking an emotional response. Repeated exposure to media therefore pushes value levels towards the extreme ends of the value importance spectrum; that is, people become more strongly opinionated. The strength of the effect that media exert on the value system of a listener is modulated by (**D**) [*media_infuence*].

The current experiment explores how selective exposure, media biases and media influence affect agent value systems on a macro-level. This experiment is designed to compare cross-sectional slices of the distribution of value levels within an agent population. Specifically, snapshot of value level distributions are made in the first interaction round and compared with snapshots taken in the last (2000th) round. This will help to assess how value level distributions have changed after many rounds of media exposure under different media variable settings. The first experimental setup is described as setup I = [*low **A**, low **B**, low **C**, low **D***]. The second experiment setup is described as setup II = [*high **A**, high **B**, high **C**, high **D***]. It is expected that II leads to a higher degree of polarization in value levels than I. The third, and final, setup III = [*high **A**, high **B**, high **C**, low **D***] will be compared with II in order to judge the effect of **D** on the development of value levels within an agent population.

This leads to the formulation of the following hypotheses:

H3.1 = Intentional exposure is positively related to the degree of polarization present within an agent population.

H3.2 = Mass media bias is positively related to the degree of polarization present within an agent population.

H3.3 = The strength of the filter bubble effect is positively related to the degree of polarization present within an agent population.

H3.4 = Media influence interacts positively with (i.e. boosts) the effects of mass media bias, filter bubble and intentional exposure on the polarization of agent value systems.

The results of experiment #3 can be found in Appendix 6.3. Upon inspection of the violin boxplots presented in Appendix 6.3, one is able to conclude that the politically-laden value types (i.e. UNI, BEN, CT, SEC, POW) are sensitive to the hypothesized polarization-effect of media. Figures 4, 5, 6, 7 and 8 (Appendix 6.3) show that these political values bifurcate into a bimodal distribution under setup II but not under I (with the only exception being POW, see Figure 8 in Appendix 6.3). This observation partially supports H3.1, H3.2 and H3.3 as these postulate that higher levels of media exposure variables lead to a polarization of value levels. The term "partially" is used here because the hypothesized polarization effect applies only to the political value types.

It is worth noting that, judging from the position of the median in the boxplots, higher media variable settings seem to generate a liberal bias. More specifically, when comparing II with I, it can be seen that the median of the liberal values (i.e. UNI, BEN) is pushed towards the higher importance region of the value level continuum (> 0.5), whereas conservative values (i.e. CT, SEC, POW) are pushed down towards the lower end of the spectrum (< 0.5). This also explains why CET attitude levels tend to be more positive (> 0.5) under II than I. This liberal bias can be explained by the fact that agent value systems are calibrated on the basis of statistics that describe the distribution of views within Dutch society (Aalbers, 2006). Media tends to cultivate cultural standards, and since Dutch society is liberal this explains why media exposure leads to the liberal bias described in this paragraph.

Lastly, with regards to H3.4, the reader is referred to Table 25 which provides an overview of Bimodality Coefficients (BCs). A BC provides an indication of how bimodal a distribution of measurements is (Pfister, Schwarz, Janczyk, Dale, & Freeman, 2013). The higher the BC, the more extreme the level of bimodality. Upon analysis of Table 25, it stands out that the BCs of value measurements under III are more extreme than under II for the political values (i.e. UNI, BEN, CT, SEC, POW). This indicates that [*media_influence*] does indeed boost the polarizing effect of the other media exposure variables. Hence, H3.4 is supported.

Table 25. *Bimodality Coefficients of Metric Measurements for Experimental Setup II and III.*

	BC_{II}	BC_{III}	BC_{II} / BC_{III}
ACH	0.30	0.36	0.81
BEN	0.71	0.43	1.65
CT	0.63	0.33	1.90
HED	0.27	0.48	0.57
POW	0.73	0.56	1.31
SEC	0.67	0.39	1.72
SD	0.33	0.41	0.81
STM	0.28	0.41	0.67
UNI	0.74	0.49	1.49

BC_{II} = Bimodality coefficient for setup #2.
BC_{III} = Bimodality coefficient for setup #3.

5.3.5 *Experiment #4 : System Instability*

Experimental Narrative & Hypotheses

Energy consumers find themselves operating within an environment that exhibits a degree of disorder. This disorder is a function of the exogenous variables (**A**) [*environmental_instability*], (**B**) [*economic_instability*], (**C**) [*social_instability*] and (**D**) [*technological_change*]. Each of these variables is proportionally related to the degree of disorder present in the simulated world. Disorder serves as a proxy for the occurrence frequency and impact of disruptive events. Disruptive events are those that destabilize a system's state of functioning. Destabilization refers here to the rapid and broad-scale reconfiguration, or reorganization of system components.

Values serve to reduce complexity and guide behaviour during decision-making under uncertainty. The importance of a value is judged on the basis of its ability to guide the decision-making process towards the realization of valuable outcomes. System instability increases the frequency of agents being exposed to situations wherein they are forced to make decisions under uncertain circumstances. Hence, system instability puts the configuration of agent value systems under pressure.

The following experiment tests how various aspects of system instability affect the value and attitude systems of agents. The current experiment is characterized by a cross-sectional design. Specifically, a snapshot of the distribution of value levels in the agent population at *t* = 0 is compared to a snapshot of the same distribution at t = 2000 (where *t* = interaction round). Doing so should reveal how values have changed over the course of 2000x interaction rounds under different setting combinations for {**A**, **B**, **C**, **D**}. Experimental setup I = [*low **A**, low **B**, low **C**, low **D***] serves to generate a baseline scenario for assessing the effect of systemic instability. Experimental setup II = [*high **A**, high **B**, high **C**, high **D***] is expected to increase the variability in the population distribution of particular value levels compared to setup I. This is because the stability of I provides agents with a peace and clarity of mind, which fosters the emergence of mutual understanding. This, in turn, breeds compromise and alignment of viewpoints. On the contrary, the instability of II generates uncertainty and ambiguity which disrupts the process of consensus formation and breeds disagreement.

This leads to the formulation of the following hypothesis:

H4.1 = System instability leads to higher variability in the distribution of value levels within an agent population.

Furthermore, it is expected that system instability negatively affects the liberal value types (i.e. UNI and BEN) and positively affects those labelled as conservative (i.e. CT, SEC, POW). This expectation is based on the presumption that humans generally perceive instability, and the uncertainty it generates, as something threatening. When humans feel threatened, they tend to ascribe a higher importance to conservative values relative to liberal values.

This leads to the formulation of the following hypotheses:

H4.2 = System instability is inversely (proportionally) related to the importance ascribed to liberal (conservative) value types.

When looking at Table 26, it becomes clear that the standard-deviation of most metrics is larger for II than I. This provides partial support to H4.1, which postulates that system instability is proportional to the (population-level) variability of value measurements.

Table 26. *Experiment #4: Standard-Deviations of Metric Measurements for Experimental Setup I & II.*

	σ_{I}	σ_{II}	σ_{II}/σ_{I}
ACH	0.07	0.16	2.29
BEN	0.01	0.07	7.00
CT	0.02	0.07	3.50
HED	0.06	0.10	1.67
POW	0.01	0.05	5.00
SEC	0.02	0.03	1.50
SD*	0.16	0.06	0.38
STM*	0.11	0.06	0.55
UNI	0.01	0.10	10.00

* = $\sigma_{I} > \sigma_{II}$

Upon inspection of the visual results of experiment #4 (to be found in Appendix 6.4), it stands out that values labelled as anxiety-free, gain-promoting, self-expansive and growth-oriented (i.e. HED, STM, SD, UNI, BEN; see Figure 2 in Appendix 1) are all negatively affected by system instability. Those values classified as anxiety-based, loss-prevention and self-protective (i.e. ACH, POW, SEC, CT; see Figure 2 in Appendix

1) are positively affected by system instability. This observation supports H4.2, which states that liberal (conservative) value levels are negatively (positively) related to levels of system instability.

Lastly, an OLS regression was performed to explore the effects of the various system instability variables on the 3x attitude metrics (see Appendix 6.5 for an overview of regression outcomes). With regards to the overall quality of the 3x models, as judged by the coefficient of determination (R^2), it is striking to see that model II is only able to yield errors that are, on average, 6.73% smaller than those of using the mean as a predictor of individual EV attitude measurements (Nau, 2019). Hence, although system instability affects the EV attitude of agents, it does so only marginally. The combined effect of system instability variables seems to affect the PV attitude of agents the most ($R^2 = 0.446$, $F(4, 39995) = 8058$, $p < 0.001$).

Upon inspection of the β-coefficients, it is interesting to observe that technological change is the only variable that, when increased, leads to more positive levels of PV ($\beta = 0.043$, $p < 0.001$) and HP attitudes ($\beta = 0.022$, $p < 0.001$). In case of PV attitude, the strongest predictor is shown to be environmental instability ($\beta = -0.114$, $p < 0.001$). Technological change affects EV attitude the strongest ($\beta = -0.0185$, $p < 0.001$) and social instability is the strongest predictors of HP attitude ($\beta = -0.068$, $p < 0.001$).

5.4 A Reflection on the Modelling Process

The following section provides an epistemological reflection on the suitability of ABMs for studying belief system change. Specifically, the following question is addressed: *"what knowledge are we able to obtain about belief system change through the application of ABMs?"* This reflection is grounded in the author's experience with building the ECBCS, and is supplemented with insights obtained from academic literature.

Social science research, like the current study, tries to understand social phenomena by proceeding to build simplified representations of it (Gilbert & Terna, 2000). There are three different types of representations, namely: (i) verbal argumentations, (ii) mathematical and statistical models, and (iii) computer simulations (Ostrom, 1988). This thesis set out to better understand belief system change by building a computer simulation of it.

As noted in Chapter #1, the suitability of ABMs is assessed in terms of the value they add to testing and improving on theories that aim to explain belief system change. By constructing and experimenting with the ECBCS, the current study came across two examples of 'suitability-detractors': (i) *model uncertainty* and (ii) *validation issues*. However, the study identified two ways of potentially dealing with these suitability-detractors (particularly the one related to model uncertainty), namely: (i) *evidence-based modelling* and (ii) *evolutionary model-sampling*. Furthermore, based on the current modelling efforts, a pair of 'suitability-enhancers' is identified, namely: (i) *formal expressiveness* and (ii) *experimental unboundedness*.

5.4.1 ABM Disadvantages

Figure 18 provides an overview of the ABM construction process. As shown, there are ample of ways that an ABM may drift from being a meaningful representation of belief system change to one being inaccurate and/or false. This ostensibly harms the suitability of ABMs for systematically studying belief system change. However, there are ways to minimize the overall harm inflicted by the modelling errors depicted in Figure 18. These ways are explicated in the following section.

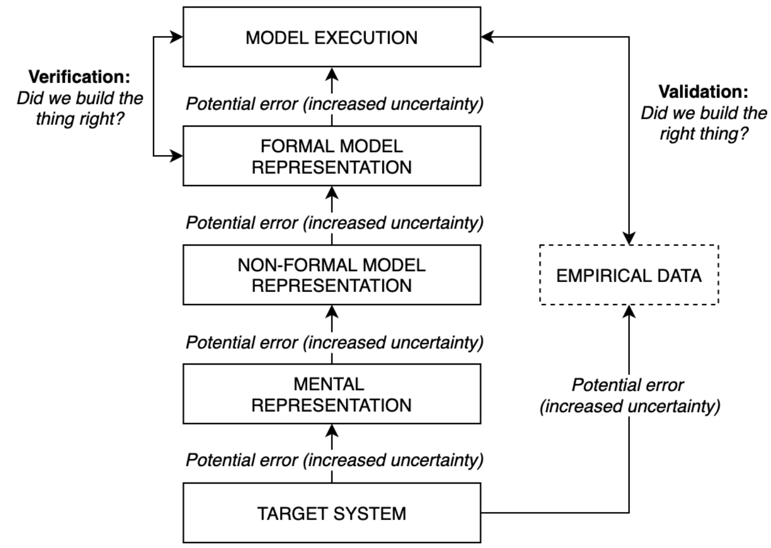


Figure 18. *Sources of Error and Uncertainty in the ABM Construction Process (partially based on Galán et al., 2009, fig. 2).*

5.4.2 Evolutionary Model-Sampling Process

The ECBCS can be considered as an instance of a near-infinite ways of constructing an ABM-representation of belief system change within an energy-system's context. The lion's share of such representations will be invalid, some of them plausible and very few of them valid (see Table 27).

During the construction of the ECBCS, the author came across a set of key decision-making steps that help explain the extreme variability in potential ABM-representations. These decision-making steps are: (i) specification of target-system boundaries, (ii) construction of non-formal model, (iii) formalization of non-formal model, (iv) implementation of formal model. ABM-representations differ from one another because of the decisions made during each of these steps.

At each step, one is confronted with selecting an option from a set of alternatives. For instance, during step (ii) one must decide upon which variables and processes to include in – or exclude from – the non-formal model. The various collections of variables and processes that could be included in the non-formal model constitute options within the 'option-set' at step (ii). Each time a decision is made (i.e. an option is selected), the size of the set of potential ABM-representations is drastically reduced. This implies that each decision made during the model construction process holds an opportunity cost, which is determined by the quantity and quality of options foregone. Ultimately, one reaches a point at which no decisions have to be made anymore; this signifies the completion of the ABM. Figure 19 visualizes this process as a recursive tree diagram where each decision-making step sprouts a collection of branches, each representing an alternative ABM design. Based on this reasoning, one may conceive of a completed ABM as a unique sequence (i.e. a vector) of options selected during each decision-making step.

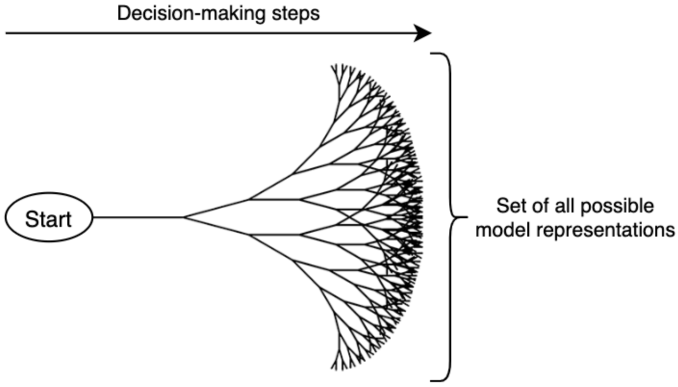


Figure 19. *Abstract Visualization of ABM Construction Process.*

Each attempt at modelling belief system change can be thought as drawing a sample of N = 1 from *a pool that contains all possible ABM-representations of belief system change* (henceforth denoted as $\mathbf{X}$). The ABM-representations within $\mathbf{X}$ can be mapped onto a fitness scale, which gauges their ability to explain or reproduce real-world belief system change. The set of representations in $\mathbf{X}$ that exhibit 'optimal' levels of fitness is denoted by $\mathbf{Y}$. Note that the set of representations that *is not* $\mathbf{Y}$ (i.e. $\mathbf{X} - \mathbf{Y}$), is vastly larger than $\mathbf{Y}$. Technically, the fitness of all possible model-representations is presumed to follow a power-law type of distribution (fat-tails); where a large majority of models is extremely unfit and only very few of them exhibit exceptional fitness. Hence, it is highly unlikely that a sample of N = 1 contains a representation that resides within $\mathbf{Y}$. However, each sample drawn from $\mathbf{X}$ potentially provides information on how to move closer towards $\mathbf{Y}$. Moving closer towards $\mathbf{Y}$ requires that for each sample drawn from $\mathbf{X}$:

A. One replicates only the successful (i.e. fitness-enhancing) features of previously drawn samples. In other words, when building upon previous work aimed at modelling belief system change, one should incorporate only the validated components of those ABMs (Edmonds, 2010; Frenken, 2006).
B. One introduces slight alterations to extant ABMs of belief system change. These alterations should ideally be backed by empirical evidence (i.e. *evidence-based modelling*), or otherwise on theoretical postulations (Edmonds, 2010). Tinkering with extant (partially validated) ABMs drives the process of trial and error which, over time, should lead to the gradual refinement of ABM-representations of belief system change (Frenken, 2006).
C. One thoroughly documents, verifies and validates the final ABM product. Future efforts at modelling belief system change should be able to select only the fittest and most rigorously tested components of the ECBCS.

Taken together, these three requirements ensure that the likelihood of, at some point, drawing a sample from $\mathbf{Y}$ is increased. The requirements represent an evolutionary-type of process, where (A) = *replication*, (B) = *variation* and (C) = *selection*. This process is therefore referred to as *evolutionary model-sampling* (see Figure 10, Appendix 2). The conceptualization of the 'evolutionary model-sampling process' is based on a synthesis of relevant academic literature (see e.g. Edmonds & Moss, 2005; Edmonds, 2010; Nikolic, 2009).

Note that the 'optimal fitness' of ABM-representations within $\mathbf{Y}$ refers to them being highly adapted to what is required from them by a user-community. The definition of fitness may change over time due to alterations in these user-requirements, but also due to a change in the nature of the belief change phenomenon itself (Edmonds, 2010). Hence, model-representations within $\mathbf{X}$ find themselves positioned on a morphing fitness landscape (see Figure 20). This implies that there will not ever be an ABM of belief system change that is *universally* and *perfectly useful*. Inversely, ABMs of belief system change will always be *locally* and *imperfectly useful*. An 'imperfectly useful model' refers to a model that is 'incomplete but useful' (Nikolic, 2009).

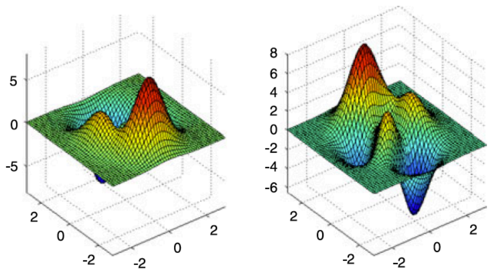


Figure 20. *Representation of Morphing Fitness Landscape (taken from van Dam et al. 2013, p. 33).*

Gauging the fitness of model-representations can be done by applying various verification and validation techniques (for an overview of these methods see e.g. van Dam et al., 2013, p. 126). Generally, the validity of an ABM is assessed by comparing model outcomes with data that describes the real behaviour of a target-system. However, obtaining credible, empirical and quantitative data on belief system change is a cumbersome endeavour. Measuring intangible psychological constructs such as beliefs presents a wide range of methodological issues, amongst which: dealing with socially desirable responses, cultural taboos, privacy, proper survey design *et cetera*. However, since this affects all types of research approaches applied to studying belief system change it does not harm the suitability of ABMs in particular.

Table 27. *Inverse Relationship between Fitness and Quantity of BSC Model-Representations.*

Fitness*	Share**
High	(Very) Low
Medium	Medium
Low	High

* = a model's fitness is a function of the extent to which it is verified and validated.
** = number of model-representations within $\mathbf{X}$ as a proportion of $\mathbf{X}$.

To conclude, ABMs are suitable tools for studying belief system change as long as models are able to build and extend upon previous models in ways explicated in the preceding paragraphs. This essentially means that ABMs are suitable as long as they are applied within a research context that involves a process of (i) inter-scientist collaboration over (ii) a long period of time, with scientist operating in (iii) different academic fields of study and (iv) cognizant of the transcendent (i.e. evolutionary) purpose of their creations (Edmonds, 2010; Nikolic, 2009).

5.4.3 ABM Advantages

The advantages of ABMs for studying belief system change are that they exhibit a high degree of (i) *formal expressiveness* and (ii) *experimental unboundedness*. The following paragraphs elaborate on this statement.

ABMs can be used to construct model-representations that are structurally very similar to the target-system under scrutiny (Nikolic, 2009). That is, ABMs are not limited to being analytically solvable (i.e. mathematically tractable), hence they are able to closely mirror the complexity and dimensionality of a target-system. This formal expressiveness increases the upside potential of modelling accuracy. In the case of belief system change, ABMs are able to provide an intuitive way of representing people as agents and beliefs as agent state-variables.

Furthermore, the formality of ABMs allows for effective codification and transfer of scientific knowledge on belief system change. ABMs can be thought of as convenient 'knowledge-capsules'; easily and reliably transferable amongst researchers, insightful to tinker with, and relatively straightforward to extend upon. Similar to scientific books or papers, ABMs communicate a theoretical narrative. However unlike paper-based media, ABMs are interactive and provide a user with a stronger experiential learning experience. Hence, ABMs can be valuable vehicles for theory transfer and development (Calder et al., 2018).

The experiments performed with the ECBCS cannot be performed in the real world either due to ethical constraints, cost-effectiveness or simply because the nature of reality does not allow it. This illustrates the 'experimental unboundedness' of ABMs in general. Though it is not possible to use the ECBCS to make accurate predictions, it does point towards classes of events that could be expected to occur in reality (Gilbert & Terna, 2000). Tinkering with the model's inputs enables one to determine the conditions upon which the emergence of certain interesting events depend. Lastly, experimenting with ABMs will often generate new questions propelling further, more intelligible, investigation of belief system change within a socio-technical system's context (Edmonds, 2010).

6 Conclusion & Discussion

This chapter presents a conclusion that summarizes and reflects upon this study's main findings. In doing so, answers are formulated to the current research questions. Furthermore, a discussion section is presented which provides a broader interpretation of the key findings and a reflection on their respective implications. The discussion section ends with delineating the current study's limitations and providing recommendations for future work.

6.1 Conclusion

This thesis set out to construct a model of belief system change and the formation of consumer attitudes within an energy system's context. The behaviour of this model was subsequently studied by experimenting with the ECBCS. Lastly, the general suitability of ABMs for systematically studying belief system change was reflected upon. The following paragraphs summarize the current findings. In doing so, they provide an answer to the main research question:

"How can belief system change and the formation of energy consumer attitudes with regards to clean energy technologies be conceptualized, and can this conceptualization be formalized and studied using an agent-based modelling approach?"

[RQ1]	*How can the mechanisms that underlie belief system change and the formation of consumer attitudes towards clean energy technologies be conceptualized?*

A belief represents a mental conviction of (i) how reality is or (ii) how it should be. The former type of belief is referred to as a factual belief or knowledge, the latter as an affective belief or value. Attitudes are formed on the basis of values and factual beliefs. An attitude represents the evaluative component of a set of factual and affective beliefs. Specifically, an attitude serves to evaluate a stimulus object or entity to determine whether to approach or avoid it.

Within an energy system's context, individuals are, to varying degrees, knowledgeable about the consequences of using a clean energy technology (CET) for the well-being of oneself and others. During deliberate decision-making, individuals combine this knowledge with that which they consider to be important or desirable in life. The attitude that emerges from this process of deliberation shapes an individual's intention to adopt a particular CET. Specifically, if the attitude is positive (negative) the intention to adopt a CET increases (decreases).

This study proposed that a CET may be understood as an assemblage of attributes; each of which may be evaluated by an observer. These attributes are *purchasing cost*, *operating cost*, *comfort*, *safety*, *environment*, *autonomy* and *privacy*. Specifically, each CET exhibits a performance on these attributes relative to other energy technologies addressing a similar consumption domain (i.e. heating & cooling, mobility, power). When a CET outperforms its competitor(s), people are more likely to adopt it. Whether the relative performance of a CET on a particular attribute is 'better' (or 'worse') depends on the subjective evaluation of an observer. More specifically, a CET may exhibit a 'higher' or 'lower' performance on some attribute, which may then be judged as 'better' or 'worse' depending on an observer's value system. The aggregation of attribute performance evaluations determines an energy consumer's overall attitude with respect to a particular CET.

It is important to note that people's decisions or actions do not always correspond with that which they value. Understanding these discrepancies calls for a conceptualization of belief systems. Factual and affective beliefs are functionally and logically interrelated forming a structure referred to as a belief system. Driven by the need to avoid the psychological discomfort of cognitive dissonance, individuals seek to structure their belief systems into coherent, or 'logically consistent' states. As long as an individual is not aware of any obvious contradictions present within her belief system, it is perceived as logically consistent. Importantly, individuals tend to prefer a logically consistent belief system over one that accurately resembles the true nature of reality. Ideological or religious dogmatism, confirmation bias and motivated reasoning are manifestations of this phenomenon.

When a person becomes aware of any discrepancies between how she acts and what she values, her belief system may change in order to restore a sense of normalcy. Generally, changing one's beliefs to accommodate for the value-behaviour gap is easier than changing one's behaviour. To resolve a value-behaviour gap, one may reduce the importance ascribed to dissonant beliefs, add more consonant beliefs as to outweigh the dissonant beliefs, or alter the dissonant beliefs to resolve the inconsistency (Nordlund, 2009).

Besides the value-behaviour gap, people's beliefs may be disrupted as a result of being exposed to information that is in conflict with the actual state of one's beliefs. For instance, someone firmly convinced that all swans are white will experience a mental trauma upon perceiving a black swan. This is an example of 'punctuated' belief system change. This study proposed that as the world that people perceive becomes more unstable and disorderly, their belief systems will be exposed to 'black-swan-type' shocks more often and more intensely.

Conversely, belief system change can also happen more gradually over time as an individual's beliefs are shaped by socialization and culturalization processes. Socialization involves processes of social influencing and learning. Culturalization encompasses the process of cultural transmission that occurs throughout life, and is especially effective at earlier stages of childhood development (Schlegel, 2011).

Language enables humans to share information with each other about the state of their belief systems. Language enables socialization and culturalization, which essentially involve the interaction of belief systems. In doing so, language drives the emergence of clusters of similar belief systems (in terms of the content and configuration of beliefs), which are referred to as (sub-)cultures.

Processes that occur within a given level of emergence affect processes occurring at a higher, or lower levels of emergence. Specifically, lower-level processes drive higher-level change, and higher-level processes constrain lower-level change. For instance, culture constrains the change occurring within the belief systems that constitute it. On the other hand, belief system change drives cultural change.

The current study identified a selection of drivers of belief system change at various levels of emergence. Key micro-level drivers are shown to be introspective contemplation and direct first-hand experiences. At the meso-level, social interaction and influence processes, along with media exposure are identified as drivers of belief system change. Lastly, systemic instability and culturalization are found to be a key macro-level drivers of belief system change. Notably, technological change forms a special omni-level driver of belief system change. In other words, technological developments may concurrently affect belief systems at a micro-, meso- and/or macro-scale.

[RQ2]	*How can the mechanisms embedded within the conceptualization of belief system change and the formation of consumer attitudes towards clean energy technologies be formalized and studied?*

Answering RQ2 resulted in the construction of the ECBCS. The ECBCS is an ABM that simulates the theorized mechanisms underlying belief and attitude change within an energy system's context. A set of experiments was conducted to explore the behaviour of the ECBCS. Specifically, hypotheses were formulated and assessed on the basis of a large variety of simulation runs. In doing so, certain outcome regularities were observed that could be linked to the manipulation of particular model parameters. The following paragraphs summarize the key insights obtained with regards to the behaviour of the ECBCS.

Under default model settings, the ECBCS does not seem to generate more than three well-defined clusters of like-minded individuals. Moreover, three distinct patterns of value change could be observed (see Figure 21). The first pattern is labelled "centrist consensus" and is characterized by the emergence of a global consensus around the viewpoint of indifference. This pattern can be observed in Figure 1 (Appendix 6.0) with the value type "Self-Direction". The second pattern is described by a global drift towards extreme viewpoints; this regularity is therefore labelled as "extremity drift". Extremity drift can be observed with the value types "Achievement", "Hedonism" and "Stimulation" (see Figure 1, Appendix 6.0). The final pattern is labelled "polarization" and is characterized by a global divergence of viewpoints. The value types that display this pattern are "Benevolence", "Conformity & Tradition", "Power", "Security", "Universalism".

Notably, the value types that tend to display a polarization pattern are those considered to be politically-laden (Piurko et al., 2011). Due to their political nature, these value types were modelled to be targeted most often by persuasive media content and to be highly responsive to variations in levels of systemic instability. These model features explain the emergence of polarization that the political value types display.

The values that display extremity drift are all classified as *egocentric* (see Figure 2, Appendix 2.0). This observation can be explained by the fact that there exist groups of individuals that ascribe a high importance to *other-oriented* or *social* value types (i.e. Benevolence, Conformity & Tradition, Security, Universalism). Within the ECBCS, antagonistic value types exert an opposing force on each other's importance levels. Antagonistic value types are those that reside on opposite ends of the BVT continuum framework (see Figure 3, Appendix 1). Thus, as self-transcendent value types increase in importance, egocentric value types decrease. Since "Achievement", "Hedonism" and "Stimulation" are not affected by the polarizing effect of media as much as the political value types, they tend to converge into a state of consensus.

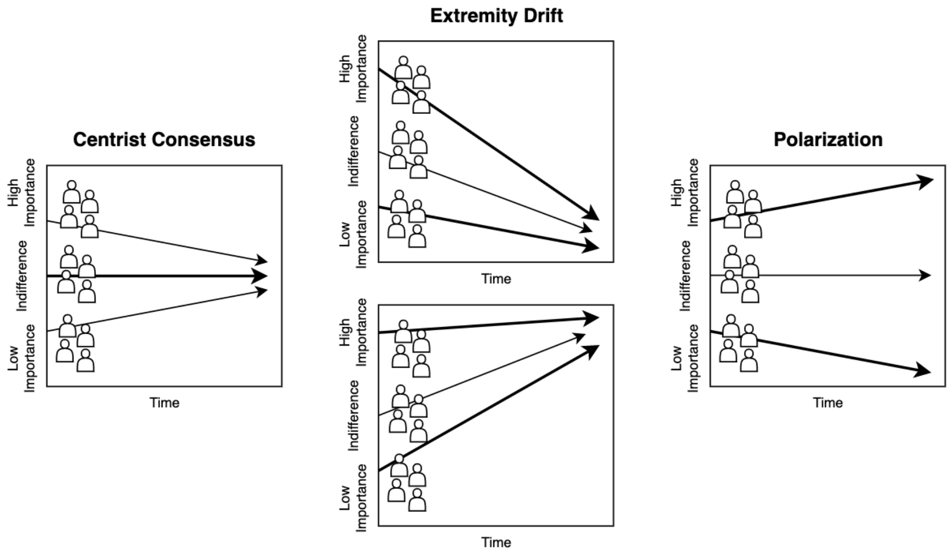


Figure 21. *Stylized Representation of Observed Regularities in Model-Generated Value Change.*

A second pattern that stood out was the higher degree of consensus observed in the attitude levels of energy consumers towards various CETs (see Figure 22). The ECBCS tends to generate a fairly tight and dense cluster of individuals that holds moderate CET attitudes. Besides these centrist clusters, there exist smaller groups of individuals that branch off into more extreme viewpoints; this is especially the case for PVs and HPs. For PVs and HPs there is more variation in the attitude levels that people hold. Under default model settings, individuals tend to be more positive about HPs and less positive about PVs. With regards to EVs, individuals seem to be more in agreement with one another (see Figure 4, 5 and 6, Appendix 6.0).

These regularities can be explained by the fact that PVs and HPs are modelled to appeal to people's biospheric and self-transcendent values (i.e. Benevolence and Universalism) more directly than EVs. People tend to be highly polarized in terms of their valuation of biospheric and self-transcendent values (see Figure 1, Appendix 6.0), which explains why people show more disagreement in their attitudes of PVs and HPs relative to EVs. EVs are proposed to cater to a broader palette of value types than PVs and HPs. EV attitudes are therefore characterized by a higher dimensionality, and thus more likely to be moderate (Tesser & Shaffer, 1990).

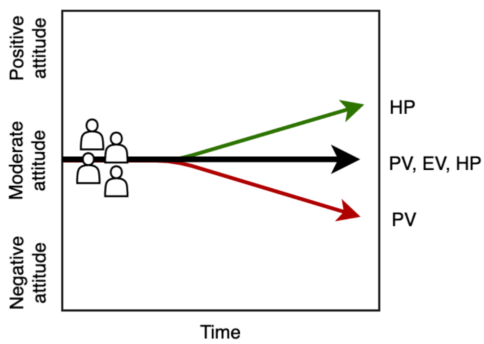


Figure 22. *Stylized Representation of Observed Regularities in Model-Generated Attitude Change.*

The ECBCS was able to reproduce the value dynamics (see Figure 2, Appendix 5.3) and higher-level structure of agent value systems (see Figure 8, Appendix 5.3) as proposed by the BVT. It was interesting to observe here that attitudes towards HPs and PVs were classified as highly progressive and self-transcendent, whereas EV attitudes were characterized as being more self-oriented and conservative. The self-orientedness of EV attitudes could be explained by arguing that EVs are highly visible and differentiated technologies that generally serve to accentuate an owner's social image (Shavitt, Lowrey, & Han, 1992). The more progressive nature of PV and HP attitudes could be explained by arguing that they constitute more radical alternatives to the technologies they aim to replace, whereas EVs and ICEVs do not differ so much apart from subtle differences in driving experience and refuelling procedures.

Other regularities in value and attitude dynamics were observed upon the experimental manipulation of model parameters related to social influence, system instability and media exposure.

With regards to the manipulation of social influence, it was observed that increasing the tolerance of individuals promotes consensus formation. Conversely, increasing the hostility of individuals bred disagreement. Lastly, levels of individualism within individuals was shown to be positively related to the variability of viewpoints *within* groups of like-minded people. These observations all correspond to *a priori* expectations formulated on the basis of Social Judgment Theory (Petty et al., 1992; Sherif & Hovland, 1961).

Furthermore, it was found that high levels of system instability led people to ascribe a higher importance to self-enhancement over self-transcendence, and cherish conservation over progression (See Appendix 6.4). Conversely, low to medium levels of instability led people to value self-transcendence and progression over their respective antagonists. As a consequence, CET attitudes are generally positive (negative) as levels of instability diminish (increase) (See Figure 10, 11 and 12, Appendix 6.4). This pattern occurs because instability is proposed to be positively related to feelings of anxiety and stress, which increase the appeal of egocentric and conservative value types (Feygina et al., 2010; Graham et al., 2009). It was also observed that the role of media was highly critical in mediating the relationship between system instability and belief system change (See Appendix 6.3). That is, media was found to be a significant driver of viewpoint polarization, especially with regards to the political value types.

Interestingly, intensified media effects were found to promote a liberal worldview when system instability variables were controlled for (i.e. kept fixed at their default settings) (see Appendix 6.3 and/or Section 5.3.4). The inclusion of cultural bias within the ECBCS can explain this observation. Specifically, mass media tend to cultivate the dominant views within a society (Gerbner, 1998; Gerbner et al., 1986). Since, agent values were calibrated according to the distribution of views present within Dutch society, which tend to be liberal (Aalbers, 2006; Piurko et al., 2011), media were inclined to promote liberal views.

In contrast to what was expected, it was observed that culture played almost no role in explaining dynamic patterns of value and/or attitude change. This can be explained by a myriad of factors, amongst which faulty formalization and/or faulty experimental manipulation. The author suspects faulty formalization to be the most likely cause of this unexpected observation (see *"Alternate Formalization of Belief Systems"*, Section 6.2.3.2).

[RQ3]	*How useful are agent-based models for building formal representations of belief system change and the formation of consumer attitudes towards clean energy technologies, and complex social phenomena in general?*

An answer was formulated to RQ3 on the basis of the author's experience with building the ECBCS and insights obtained from studying relevant academic literature (see Section 5.4). It was found that ABMs are highly versatile and, potentially, useful tools for studying belief system change *if* they are applied within a specific research context (denoted as $\mathbf{X}$). $\mathbf{X}$ can be summarized as follows: to ensure their suitability, ABMs of belief system change ought to be applied and developed within a research process that promotes evidence-based modelling, long-termism, inter-scientist and inter-disciplinary collaboration, and a highly critical stance towards the validity of the ABM-creations of oneself and of others. Essentially, ABMs of belief system change ought to be subjected to the evolutionary forces of replication, variation and selection as explicated in the description of the "evolutionary model-sampling process" (Section 5.4.2). Only then are ABMs likely to serve as powerful vehicles for scientific knowledge-accretion and theory development.

In light of $\mathbf{X}$, the scientific contribution of the ECBCS lies within (i) tinkering with components adapted from previous (partially validated) ABMs of belief change. Additionally, the ECBCS contributes by introducing (ii) entirely novel model-components that serve to inspire and offer alternative ways of thinking about belief and attitude change within a socio-technical system's context.

With regards to contribution (i), model-components such as the *Social Influence Model* (SIM) and the *Information Diffusion Process* (IDP) were replicated successfully. Subsequently, the SIM and IDP were altered slightly. The SIM was enhanced by adding representations of individualization, peer-pressure and culturalization. The IDP was augmented by integrating an individual's experience of being surprised by new information. With respect to contribution (ii), components such as the *Media Exposure*, *Introspection*, and *Attitude Formation* sub-models are not based on any previous modelling work and are therefore highly original. Further efforts at validating these innovative components should reveal their respective fitness. This should help to decide upon whether to forget or keep them when constructing novel ABMs of belief system change.

6.2 Discussion

This section starts by presenting a reflection on the potential applicability of the current experimental results. Next, the scientific and societal implications of this study are discussed. The discussion concludes by presenting a set of limitations that are subsequently used as a basis for the formulation of recommendations for future work.

6.2.1 Interpretation

It must be stressed that the ECBCS cannot be used to predict what will become valuable to people in the future. Moreover, although the ECBCS may point towards certain patterns in belief and attitude change that correspond to what is observed in the real world, this does not provide sufficient evidence for concluding that the ECBCS is able to *explain* this phenomenon. For this to be concluded, the outcomes of the ECBCS must be thoroughly validated against empirical data, which lies beyond the scope of the current study.

However, interpreting the behaviour of the ECBCS on the basis of what is observed in the real-world *does* help to gauge its usefulness as a potential seed for more elaborate, evidence-based explanatory models of belief and attitude change.

The following list consists of statements that summarize the experimental data generated by the ECBCS. The statements are subsequently interpreted in light of empirically-grounded observations:

A. *The emergence of clusters of individuals that share similar viewpoints.*

Point (A) can be interpreted as representing homophily, which describes how people prefer to spend their time with like-minded others (McPherson et al., 2001).

B. *The emergence of clusters at extreme ends of a value type's importance spectrum.*

Point (B) can be interpreted as a consequence of people's need to increase the contrast of their referent group's views and boundaries in order to strengthen its political position (Barendrecht, Harchaoui, Omlo, el Baktit, & de Ruiter, 2009). Increasing the starkness of group-boundaries in this way nurtures the emergence of polarization.

C. *The emergence of a cluster of individuals that hold indifferent viewpoints.*

Point (C) can be interpreted as representing *existential indifference*. Existential indifference describes a psychological state of "valuelessness" or a lack of commitment to values (Schnell, 2010).

D. *The collective drift of people's viewpoints towards extremity.*

Point (D) can be interpreted as a form of cultural drift (Centola et al., 2007); which can be defined as *"the tendency of a collective value system to manifest cumulative variation in a particular direction"* (Merriam-Webster, 2019a).

E. *The lower variability in attitudes towards EVs than towards HPs or PVs.*

Research points out that as the cognitive structure that underpins an attitude gains in complexity, it tends to become less extreme (Tesser & Shaffer, 1990). EVs are proposed to appeal to a broader set of values. Hence, an individual's attitude towards EVs is based on a more complex cognitive structure.

F. *The strong (polarizing) influence of media exposure on individual viewpoints.*

Point (G) corresponds to the increasing pervasiveness and intrusiveness of media in determining information flows and shaping public opinion within Dutch society (Dekker & den Ridder, 2019). The current findings correspond to the polarization of viewpoints observed within Dutch society and the contributing role of (principally digital) media in this regard (Dekker & den Ridder, 2019).

6.2.2 *Implications*

The following sections present the theoretical and practical implications of this study. Upon reading these sections, it should become clear how this study contributes to existing knowledge about belief and attitude change and what the academic and practical consequences of these contributions are.

6.2.2.1 *Theoretical Implications*

The current study makes three key scientific contributions:

1. Present an original way of thinking about and formalizing how value change happens within a socio-technical system's context.
2. Increase our theoretical understanding of how beliefs (values and knowledge) and attitudes change and how this impacts the evolution of energy systems.
3. Highlight the importance of an eclecticism approach in conceptualizing belief and attitude change within a socio-technical system's context.

Contribution #1: By combining the Basic Value Theory (BVT) (see e.g. Schwartz, 2012) with Dewey's Value Theory (DVT) (Anderson, 2018; Dietz et al., 2005; Kostrova, 2018), this thesis provides an original way of thinking about value change. In a pragmatic sense, the BVT and DVT complement one another as the former is concerned with the substantive and structural characteristics of people's values, while the latter theorizes on how values are formed and evolve.

Van de Poel (2018, p. 2) delineates five types of value change within a socio-technical system's context. The synthesis of the BVT and DVT, and the model derived from it (i.e. the ECBCS), are able to account for at least two types of value change.

(i) The emergence of new values.

Conceptually, if the universal requirements of human well-being and existence were to change, then the emergence of a qualitatively distinctive value type could occur. To illustrate, some argue that there exists an eleventh BVT value type coined "Spiritualism". This value type is representative of exemplary values that relate to the pursuit of meaning in life (Schwartz, 1994). If the pursuit of meaning can be shown to address any of the aforementioned universal requirements, then "Spiritualism" would indeed constitute a novel BVT value type. The emergence of such a qualitatively distinct BVT value type lies beyond the current capabilities of the ECBCS.

(ii) Changes in what values are relevant for the design of a certain technology.

Within the ECBCS, energy consumers may obtain a different, potentially more accurate, factual understanding of the consequences of producing, using and disposing of a CET. When this happens, a CET will come to appeal to a different set of values than before. This mechanism constitutes a representation of value change type (ii).

(iii) Changes in the priority or relative importance of values.

Type (iii) can be represented by changing the configuration of agent value systems within the ECBCS. This refers to sorting an agent's value types according to their importance level and/or emotional intensity. Based on the DVT, the importance levels of value types may change in response to one's exposure to unfamiliar and/or disruptive events.

(iv) Changes in how values are conceptualized.

The richer, or broader, the conceptualization of a particular BVT value type, the more exemplary values fall within its domain. Although not explicitly represented within the ECBCS, one could imagine that the attractiveness of – or public support for – a particular BVT value type increases as its conceptualization becomes richer. Hence, BVT value types could, in alternative ABMs of belief change, be described in terms of their conceptual richness which would account for value change type (iv).

(v) Changes in how values are specified, and translated into norms and design requirements.

One could think of (v) as an instance of a 'technology-mediated revision of beliefs'. For instance, technological developments within the mobility industry might lead to the introduction of technologies that drastically decrease the (relative) environmental performance of EVs. To illustrate: EVs are currently considered as environmentally-benign technologies. However, the introduction of a new type of battery with a much lower ecological footprint may render the current design of EVs unacceptable from a perspective of environmental sustainability. This kind of change in value specification is also not formally represented within the ECBCS.

Contribution #2: By combining theories from cognitive and social psychology, sociology, philosophy and complexity science, this study has shown how beliefs and energy technologies & infrastructures are tied up with one another in a coevolutionary process. The conceptual model presented in this study zooms in on a particular aspect of this coevolutionary process, namely: the process by which the beliefs of energy consumers lead to the formation of attitudes towards the adoption of clean energy technologies.

A distinctive quality of the conceptual model presented in this study is that it lends itself for formalization. Formalization enables testing the assumptions embedded within a model on the basis of computer simulations. The insights obtained from these simulations contribute to our understanding of belief and attitude change. The work done as part of this thesis also contributes to our understanding of how ABMs can best be implemented to increase our knowledge with respect to belief change and related complex social phenomena.

Contribution #3: This study has shown that it is desirable to adhere to an eclecticism approach when constructing a "generative" conceptualization of belief and attitude change within a socio-technical system's context. Eclecticism is understood here as an integration of theories stemming from different disciplines with the objective of increasing a theoretical framework's explanatory power (Foss, 2000).

6.2.2.2 Practical Implications

Belief systems guide technological and institutional developments which ultimately dictate how resources are extracted from and discarded to the Earth's biosphere. It is through the collective purpose and value we ascribe to various aspects of reality that we are able to transform it so it caters to our needs. If we are to transform our energy systems, we must understand, at a fundamental level, how humans perceive and evaluate the world around them. Identifying and establishing the mechanisms that underlie belief formation and change may foster the sustainability transformation of our energy system in the following ways:

Framing: Recognize that framing, rather than substance, determines what values are targeted and potentially influenced by a particular message. The right framing of a message can activate the "hot" information-processing route, which addresses people's affective belief or value systems. To avoid a backlash, communication aimed at promoting the need for an energy transition should be framed in ways that appeal to strongly cherished values within a society or societal segment. When framing messages, one must be extremely wary of unintentionally buttressing extant ideological fault lines and setting in motion a process of polarization or undesired extremity drift.

Value Change Proof Decision-Making: Understand that what we value (and know) today, is very likely to be different to what we will value (and know) in the (far-off) future. Acknowledging that the status of value judgments is to some degree dependent on historical context (Baghramian & Carter, 2018) facilitates 'value-change-proof' decision-making. More specifically, strategic decisions made in the present must safeguard the adaptability, flexibility and/or robustness of energy systems to changing values (van de Poel, 2018).

Decisions made today must not (unnecessarily) restrict the future decision-space. One must avoid making decisions that could lead to (deep) techno-institutional lock-ins and system-level inflexibility (i.e. fragility). Decisions must be geared towards maintaining a higher level of redundancy (or 'optionality') within energy systems. This ensures that when values drift and begin to conflict with system functioning, there exists more room to manoeuvre, i.e. more potential for change, within the energy system's boundaries.

Stated in system dynamic's terms, the energy system should be provided with a steady input-flow of innovative technologies. Furthermore, at any point in time the system's state should be characterized by a highly diversified portfolio of technologies. Over time, technical artefacts that show strongest fit with individual value systems should be preferred and therefore selected over those that show a weaker fit. Based on this reasoning, one can see how the co-evolution of values (or beliefs in general) and the technical energy system may be managed.

6.2.3 Limitations & Recommendations

There current study is characterized by several limitations which deserve attention. The current section is structured according to various types of limitations. The limitation types are: conceptual, formal, and methodological. Avenues for future work are provided on the basis of these limitations.

6.2.3.1 Conceptual Limitations & Recommendations

Theoretical Eclecticism: The current theoretical framework is comprised of a diverse set of theories stemming from different disciplines. The complexity that characterizes belief and attitude change seems to warrant such theoretical eclecticism. However, the criteria applied by this study that dictate the inclusion or exclusion of particular theoretical elements are vague. This increases the risk of combining theories that are conceptually inconsistent and ending up with a tapestry of unconnected insights (Foss, 2000). For instance, combining the BVT with Dewey's Value Theory is, from a philosophical perspective, highly disputable. Future work aimed at modelling belief and attitude change should attempt to specify clear selection criteria before constructing a theoretical framework. This should increase the likelihood of ending up with a more integrative synthesis of theoretical elements (Foss, 2000).

Value Conceptualization: Values and value change are conceptualized on the basis of an integration of Basic Value Theory (BVT) (see e.g. Schwartz, 2012) with Dewey's Value Theory (DVT) (Anderson, 2018; Dietz et al., 2005; Kostrova, 2018). However, there are many other conceptualizations one may have chosen to build a representation of belief and attitude change within a socio-technical system's context (Hills, 2002; Kilby, 1993; Kluckhohn, 1962; Kostrova, 2018; Rabinowicz &

Rønnow-Rasmussen, 2015; Rokeach, 2008; Seligman, Olson, & Zanna, 1996; Swierstra, 2013).

Other conceptualizations make a distinction between:

- *Terminal* (intrinsic worth) and *instrumental* (extrinsic worth) values (Rokeach, 2008);
- Values that are *relational* (a value that is valuable for someone or something) and *non-relational* (a value that knows no referent entity) (Rabinowicz & Rønnow-Rasmussen, 2015);
- *Evaluative* (belief in the "right") and *worth* values (belief in the "important") (Kilby, 1993);
- Values with a *moral* (indisputable) versus *non-moral* (disputable) status (Swierstra, 2013);
- *Institutionalized* (social) values versus *personal* values (Kluckhohn, 1962).

It would be interesting to integrate some of the distinctions in novel models of value change to see whether there are significant differences in the outcomes they generate.

Conceptualizing Belief-Behaviour Link: Another limitation is the missing link between beliefs and behaviour. Ample literature suggest that these two are reciprocally related to each other (Ajzen & Fishbein, 1975; Bohner & Dickel, 2011; Byrka, 2009; Grube, Mayton, & Ball-Rokeach, 1994; Schwarz & Bohner, 2007; Tesser & Shaffer, 1990).

Within the ECBCS, behaviour may be represented as acquiring and/or using a CET. For instance, it might be that the acquisition and/or usage of an EV leads to a more positive attitude towards PVs. An EV driver will have a relatively higher demand for electricity. PVs are able to supply this in a carbon-lean and cost-effective way. If the reasons for buying and driving an EV are based on environmental and/or economic considerations, then it is likely that the acquisition of the EV will enhance the attractiveness of PVs. A logical extension of the ECBCS would therefore be to include a representation of intentions and behaviour.

Moreover, the influence of someone's direct (first-hand) experiences with the world on her beliefs is also not represented within the ECBCS. This is undesirable since individuals construct their understanding of the world by actively engaging with it (see e.g. Bada & Olusegun, 2015). This means that the way in which reality 'kicks back' in response to someone's actions provides that person with meaningful information upon which they may revise or consolidate their beliefs.

Including a representation of behaviour also allows for modelling other forms of energy consumer behaviour, such as: energy savings behaviour or the occurrence of public demonstrations against or in favour of some energy infrastructure development project.

Conceptualization of CETs: Another pair of limitations can be found in the conceptualization of CETs as assemblages of attributes.

The current version of the ECBCS knows no representation of the 'aesthetic performance' of a CET. Humans are generally drawn to aesthetic objects, and repulsed by ones that are unsightly. Aesthetics can therefore be considered as serving a utilitarian attitude function. To illustrate the relevance of this tech-attribute, consider the efforts allocated towards improving people's attitude of PVs by increasing their aesthetics (Gupta, Langelaar, Barink, & van Keulen, 2016).

Agents build a factual understanding of CETs by obtaining knowledge about their performance relative to some 'competitor technology'. A CET's relative performance levels will change if it is compared to a different technology, which consequently alters an agent's attitudes. For instance, when comparing EVs to ICEVs, the former generally outperforms the latter in terms of environmental performance. However, when comparing EVs to trains, then this is not so obvious anymore. It is questionable whether, in reality, people's attitudes are influenced this heavily by making such comparisons. A potential way to remedy this issue is by constructing attitudes based on a set, or collection, of competitor technologies instead of only one.

Conceptualizing Message-Thought Inconsistencies & Context-Dependency of Belief Change Processes: The ECBCS presumes that energy consumers interact with each other in a sterile and neutral environment with little to no influence of contextual factors such as social role expectations and/or norm systems (Sunstein, 1996). In doing so, the ECBCS assumes that what energy consumers communicate is *more or less* the same as what they think. 'More or less' is italicized here because the ECBCS does include a mechanism that induces a stochastic error in the messages exchanged between agents: hence, *message ≈ thought*. However, what humans say is often different from what they think or feel about something. This discrepancy is referred to here as the *Message-Thought Inconsistency* (MTI).

Representing MTI-inducing processes such as politically-correct or socially-motivated belief communication, self-censorship and/or belief falsification is important because it distorts people's perception of what others are *actually* thinking. These processes may give rise to *'The Naked Emperor'* phenomenon, where people believe in something because they think other's do as well, but no one actually does.

The MTI may vary in continuous fashion across different contexts. For instance, talking with one's parents or closest friends should reduce the MTI, whereas someone engaged in a tactical business negotiation may exhibit a higher MTI. Moreover, some thoughts may not even be discussed with closest friends or family due to the existence of social and/or cultural taboos (Fershtman et al., 2011). In this case beliefs are muted and are therefore unable to be revised or consolidated.

Moreover, the viewpoints that people hold with regards to their values may also be context-dependent (Dietz et al., 2005). Specifically, a person may cherish a value in one situation, but downgrade its importance in another. Additionally, the volatility that characterizes the change in someone's viewpoints across situations may differ across actors (Dietz et al., 2005).

One way to represent the context-dependency of MTI and value change is by introducing *interaction arenas*. An interaction arena is a set of rules (i.e. norms) that dictate how agents are expected to behave within a particular situation. These rules become activated when an agent finds itself operating within an interaction arena's boundaries (i.e. sphere of influence). Some examples of interaction arenas are: work, home, public spaces, the internet. To put it differently, the specification of interaction arena's enables a representation of how contextual features embedded within various social situations trigger people to take on particular social roles that consequently affect how they reason, evaluate and behave (Dietz et al., 2005).

Personality differences may determine the extent to which someone obeys or disobeys the norms present within an interaction arena. Over time, these norms may change in response to agent's deciding to obey them (i.e. consolidation) versus challenge them (i.e. revision).

To conclude, including a representation of context-dependency enhances the realism of ABMs of belief and attitude change. This can be done by introducing so-called interaction arenas.

Conceptualizing Informational Filters: The ECBCS assumes that agents filter out 'hot' information that is dissimilar to their own viewpoints, and are biased towards discussing values that they cherish or detest rather than those that they are indifferent to. The ECBCS also presumed that agents disregard cold information that is not surprising enough. Although empirically sound, these filters do not sufficiently encapsulate the complex ways in which humans allocate their attention and process incoming information.

Adding informational filters should enhance the realism of models like the ECBCS. Some examples are provided by Sobkowicz (2018), namely:

- *Priming filters:* these could model how people are drawn to pay attention towards information that is familiar.
- *Primacy* and/or *Recency filters:* these could formalize how information that is provided at the beginning or at the end of a message enjoys a higher salience.
- *Simplicity filters:* these could be implemented to represent how people prefer to discuss easy-to-grasp topics over those that are complex (see e.g. the 'Law of Triviality').

An illustration of how such filters could be applied within the ECBCS is in the agent search for factual information about CETs. Applying, for example, a simplicity filter would enable agents to only seek out information that is easily understandable to them. For instance, obtaining a solid understanding of the environmental performance of a CET may require a technical background and a propensity to think deeper about the 2nd and 3rd order effects of using a technology. This brings with it a level of complexity that most people do not seem to find appealing. Hence, future work could aim to model a selection of these filters to see how belief and attitude change processes unfold under their influence.

Including a Representation of Time Discounting: Humans tend to value the present over the future (Frederick & Loewenstein, 2002; Harris & Roach, 2017). This is important to take into account when trying to understand how humans evaluate CETs. Adopting a CET generally involves making a trade-off between incurring costs in the present and obtaining benefits in the future. For instance, consider someone that wants to buy either an ICEV (€15,000) or an EV (€20,000). The EV is €5000 more expensive, but saves the buyer €150 per month of fuelling costs (€1,800 per year). The buyer is likely to evaluate the EV as less positive than the ICEV, even if adopting the EV offers a 36% annual return. In this example, the buyer is implicitly applying a mental discount rate [r] of $r > 36\%$; which, from a *homo economicus* standpoint, is considered highly unreasonable. Note that this example is adapted from Harris & Roach (2017, p. 299).

The example in the previous paragraph highlights the importance of including a representation of this mental discounting phenomenon in models like the ECBCS. Currently agents ascribe equal weight to a CET's purchasing cost (immediate consequences) and operating cost (non-immediate consequences). However, it would be more realistic if agents were programmed to be more sensitive to the performance levels of technology attributes that involve immediate consequences for their well-being.

Representation of Spatial & Temporal Dimensions: The ECBCS represents the passage of time as a sequence of discrete interaction rounds. In order to enhance its realism, simulation steps should ideally represent actual temporal units such as days, weeks or months. Altering the temporal representation of the ECBCS requires one to think about how frequently events occur that potentially induce BSC. As noted gradual BSC takes months, often years to manifest. Sudden (punctuated) BSC may take as little as a few seconds (or minutes) to happen, but occurs much less often than the more gradual form. Technically, one might apply a Poisson stochastic process to model the occurrence of 'belief change inducing events' over a specific time-interval. The challenge here lies in estimating the parameters of such a Poisson process; that is, deciding on how often a person is likely to experience a 'belief-changing event'.

Another criticism of the ECBCS is that is does not explicitly represent geographical space. Ideally, users of the ECBCS would like to apply it to study belief change and energy consumer behaviour within the boundaries of a specific region (like a city). Hence, integrating a representation of geological space would increase the practical value of the ECBCS. This may be done by mapping the social network onto a collection of geospatial layers using a GIS-approach (Balta-Ozkan, Yildirim, & Connor, 2015; Metcalf & Paich, 2005; Radil, Flint, & Tita, 2010). Figure 23 provides a simple illustration of this. Spatially explicit models of CET adoption have already been built (see e.g. Krebs, 2017; Robinson & Rai, 2015), it would be interesting to combine a representation of social networks and belief change processes with such models.

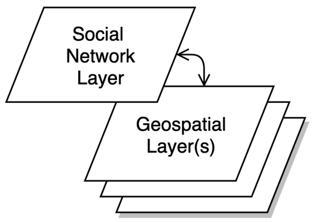


Figure 23. *Nesting Social Network in Geospatial Layers.*

Introducing a Higher Granularity in Levels of Analysis: Currently, the ECBCS makes a distinction between three levels of analysis (micro, meso, macro). However, it can be argued that the addition of an extra tier in between the micro and meso levels may enhance the model's realism.

Specifically, agents can be grouped into *households*. Intrahousehold dynamics and characteristics, such as the number of people present within a household and their respective age and gender, will have a notable impact on the belief systems of household members (Gotts & Polhill, 2017). The content and configuration of belief systems in turn influences energy consumption behaviour. Thus, future work could decide to include a representation of households as distinct micro-level systems within models of belief change and consumer energy behaviour.

Conceptualizing Demographic Dynamics: The ECBCS forms a model-representation of intragenerational belief change. It would be interesting to extend the ECBCS by including a representation of intergenerational dynamics. For instance, enabling agents to age and generate offspring would enable one to simulate how parents shape the beliefs of their children. It also allows for representing how agents, as they grow older, become less receptive to the forces of socialization and culturalization. Lastly, it would be possible to spawn agents with personalities based on a combination of the personality characteristics of their parents. Personalities dictate the various propensities and idiosyncrasies of an agent with respect to how it adopts, revises and/or consolidates its beliefs.

Furthermore, the current version of the ECBCS does not allow the social network in which the agents are embedded to change over time. In reality, however, people be- or defriend others all the time. In addition, a dynamic social network enables representing the in- and outflux (migration/immigration) of agents. This may increase the practical value of the ECBCS since, for instance, DSO's might be interested in assessing the effects of mass urban migration on the energy behaviour of citizens. Thus, including within ABMs a representation of these demographic dynamics and intergenerational belief change processes forms an interesting avenue for future work.

Conceptualizing Fake News: Fake news, defined here as *"fabricated information that mimics news media content in form but not in organizational process or intent"* (Lazer et al., 2018), is a relatively new phenomenon that should be taken into account when studying belief system change. The ECBCS does not formally represent this phenomenon, which can be thought of as a limitation. Fake news distorts and disrupts the construction of a collective understanding of how the world is and how it should be. Fake news has been shown to impact political (electoral) processes, and is argued to increase public cynicism and apathy with respect to uncovering the 'truth' (Lazer et al., 2018). It is also a driver of extremism (Lazer et al., 2018). It might be interesting for future work to model the effects of fake news on the belief systems of agents and their consequent behaviour within socio-technical systems.

Including Awareness Campaigns & Policy Interventions: A user of the ECBCS is currently not able to simulate the effect(s) of policy interventions (such as awareness campaigns) on the belief systems of energy consumers. To increase the practical value of the ECBCS, future work could aim to include such functionalities.

6.2.3.2 Formal Limitations & Recommendations

Following the TAPAS & KISS Principles: Although the ECBCS includes parts taken from previous models of belief and/or attitude change, it includes many more features whose formalization is justified primarily in terms of their 'surface plausibility' to the modeller (Edmonds, 2010). This resulted in a somewhat idiosyncratic formalization of theoretical propositions (Frenken, 2006). This implies that the modeller may have lost sight of the *"Take A Previous model and Add Something"* principle during the construction of the ECBCS. This can be considered a limitation because the higher a model's idiosyncrasy, the longer it takes to construct and the harder it becomes to communicate its workings (Frenken, 2006).

The idiosyncratic nature of the ECBCS diminishes its usefulness for people other than the one's involved in its construction. Stated differently, the ECBCS generates *personal* rather than *public* knowledge (Edmonds, 2010). Hence, the ability of the ECBCS to contribute to the progressive evolutionary model-sampling process (described in section 5.4.2) is reduced.

In light of the evolutionary model-sampling process, one ideally builds on validated formalizations of previous models and adds to them features according to the *"Keep It Simple, Stupid"* principle. Adding too many features increases the risk of building a model that is unnecessarily complicated. It is therefore recommended that future work aimed at modelling belief and attitude change strictly follow the TAPAS & KISS modelling principles.

Alternate Formalization of Belief Systems: The ECBCS formalizes a viewpoint as a numeric. It can be argued, however, that it is more realistic to formalize viewpoints as a continuous interval or even a probability density function (PDF), as prescribed by Bayesian approaches to modelling belief change. The range or PDF representation of viewpoints enables more accurate formalization of the ambiguity and uncertainty related to one's beliefs (Allahverdyan & Galstyan, 2014; Kahan, 2016; Sobkowicz, 2018). It also enables a formalization of the effect of culture on belief change that corresponds more closely to the way in which culturalization is conceptualized (see *Culturalization*, Section 2.3.6.1).

Another interesting way of representing belief systems is provided by the InnoMind architecture (Schröder & Wolf, 2017; Wolf et al., 2015). InnoMind is a connectionist framework that facilitates simulating multi-level belief change processes. InnoMind is able to model parallel constraint satisfaction processes which closely resemble the associative structure of the human brain. Thus, future work could consider combining a connectionist with a (quasi-)Bayesian approach when attempting to model belief system change.

Parameterization & Calibration Issues: Construction of the ECBCS often necessitated the inclusion of arbitrary assumptions to obtain a 'whole' and functioning model. Most of these assumptions are grounded in the author's intuitions. Examples of such assumptions are the specification of scale parameters (i.e. weights, scalars) in many of the formulae used throughout the model's procedures. Moreover a set of shape parameters (see Table 14, Appendix 1) is specified, whose calibrations are not based on empirical work either. The effects of these assumptions on model outcomes has not been adequately explored, which increases the likelihood of unwanted simulation artefacts (Galán et al., 2009). Future work could aim to limit the inclusion of arbitrary (or 'accessory') assumptions to a minimum as to avoid inflating the probability of generating artefacts (Galán et al., 2009). It could also try and assess the relative impact of changing the accessory assumptions on model outcomes by testing them using a sensitivity analysis (ten Broeke et al., 2016).

Existence of Structural Uncertainties: It is uncertain how the structural design of the ECBCS as a whole, and the algorithms that constitute it, affect model outputs. As can be seen in Figure 1 (Appendix 2), the ECBCS loops through a sequence of processes. The execution of a process, on its part, involves running through an orderly sequence of operations. The way in which the ECBCS and its constituent processes are structured is largely arbitrary. One might ask how the model behaves when processes are organized differently, or when processes are designed in a different way.

Furthermore, it is uncertain how the design of equations affect model behaviour. Equations can be multiplicative or additive, they may involve thresholds (discontinuities) or not, and are parameterized in a certain way. All of these decisions affect model outcomes in some sense. The chance that they unwantedly distort model outcomes is very much present.

Ideally, future work experiments with different model structures as to gauge their effect on model behaviour. It might be needed to scale down the modelling scope, as dealing with this structural uncertainty becomes extremely time consuming with large models.

6.2.3.3 *Methodological Limitations & Recommendations*

Limited Analysis of Model Behaviour: A proper theory exposition requires a near complete understanding of a simulation model's behaviour (Edmonds et al., 2019). However, the number of processes and parameters included in the ECBCS was too large to meet this requirement. Hence, it is likely there still exist a large part of the model's behaviour space that remains unexplored. Future work should take greater care to keep models of belief change small and simple to avoid inflating a model's behaviour space beyond practical proportions.

Brittleness of Conclusions: The current design of model experiments was limited by the computational resources available to the modeller. This meant that the number of variables to be included within model experiments had to be capped. It also meant that the manipulation of model parameters had to be dichotomized. This ruled out the ability to adequately test the conditions under which certain hypotheses are to be accepted or refuted. To put it differently, the limitations present within the current experimental designs increase the fragility of what is established (Edmonds et al., 2019). To remedy this issue, future work should aim to limit the size and scope of its ABMs so that experiments do not have to be so coarsely designed. This should help to test a collection of hypotheses with better insight into the conditional properties that underlie their refutation or acceptance.

Lack of Empirical Validation: An important objective of this study was to study the behaviour of the ECBCS itself, rather than processes of belief and attitude change in the real-world. This is not a limitation per se. However, in order to increase the practical usefulness of the ECBCS it would be interesting to validate the outcomes it generates against empirical data.

In recent times, humanity has witnessed the digitization of many, if not all, aspects of human social life. The consequent proliferation of social data enables researchers to build datasets that document and quantify belief dynamics on an unprecedented scale and level of detail (Sobkowicz, 2018). This allows researchers to take models of belief change and validate them against empirical data. The author sees fruitful avenues for future work in this regard.

Limitations of Sensitivity Analysis: The current study implemented a regression-based global sensitivity analysis to critically assess the behaviour of the ECBCS. However, the regressions performed showed a poor fit in terms of R^2 (see scatterplots in Appendix 4.2). The assumptions on which OLS regressions are based do not harmonize with the existence of non-linearities and multi-level complexity present within the ECBCS (ten Broeke et al., 2016). This explains the poor performance of the regressions implemented in the current study. A non-parametric GSA approach (such as Sobol's variance decomposition) (see e.g. Prieur & Tarantola, 2017; Saltelli, 2002) could prove to be a better (more insightful) technique for decreasing model outcome uncertainty. This approach can be extended by applying it to model outcomes over multiple time steps and multiple model repetitions (see e.g. Ligmann-Zielinska & Sun, 2010).

Advantages of Multi-Modelling: The author admits that the target-system addressed by the ECBCS may be too complex to capture within a single model-representation. This inadvertently increased the quantity of assumptions that had to be made in the completion of the model.

Ideally, the current conceptual model of belief and attitude change is subdivided into a set of modules, each of which is formalized within a distinct modelling-representation. These smaller scale models could subsequently be coupled with one another within a multi-model environment (Bollinger, Davis, Evins, Chappin, & Nikolic, 2018). Within this multi-model environment, inter-scientist collaboration may be promoted by constructing an interactive database of model-representations that enables modellers to conveniently review and improve upon each other's work.

7 References

Aalbers, T. (2006). Waardenoriëntaties, wereldbeelden en maatschappelijke vraagstukken. Verantwoording van het opinieonderzoek voor de Duurzaamheidsverkenning "Kwaliteit en Toekomst". (p. 351). Retrieved from Milieu- en Natuurplanbureau website: https://www.pbl.nl/sites/default/files/cms/publicaties/550031002.pdf

Abelson, Robert P. (1979). Differences Between Belief and Knowledge Systems. Cognitive Science, 3(4), 355–366. https://doi.org/10.1207/s15516709cog0304_4

Abelson, R.P., & Carroll, J. D. (1965). Computer Simulation of Individual Belief Systems. American Behavioral Scientist, 8(9), 24–30. https://doi.org/10.1177/000276426500800908

Abrahamse, W., & Steg, L. (2009). How do socio-demographic and psychological factors relate to households' direct and indirect energy use and savings? Journal of Economic Psychology, 30(5), 711–720. https://doi.org/10.1016/j.joep.2009.05.006

Ajzen, I. (1991). The theory of planned behavior. Organizational Behavior and Human Decision Processes, 50(2), 179–211.

Ajzen, I., & Fishbein, M. (1975). Belief, attitude, intention and behavior: An introduction to theory and research. Reading, Massachusetts: Addison-Wesley.

Alanen, L. (1988). Rethinking Childhood. Acta Sociologica, 31(1), 53–67. https://doi.org/10.1177/000169938803100105

Allahverdyan, A. E., & Galstyan, A. (2014). Opinion Dynamics with Confirmation Bias. PLoS ONE, 9(7), e99557. https://doi.org/10.1371/journal.pone.0099557

Amblard, F., & Deffuant, G. (2004). The role of network topology on extremism propagation with the Relative Agreement opinion dynamics. Physica A: Statistical Mechanics and Its Applications, 343, 725–738. https://doi.org/10.1016/j.physa.2004.06.102

Anderson, E. (2018). Dewey's Moral Philosophy. In E. N. Zalta (Ed.), The Stanford Encyclopedia of Philosophy (Fall 2018). Retrieved from https://plato.stanford.edu/archives/fall2018/entries/dewey-moral/

Antonides, G., & van Raaij, F. W. (1998). Consumer Behaviour. A European Perspective. New York: John Wiley & Sons, Ltd., Publication.

Armitage, C. J., & Conner, M. (2001). Efficacy of the Theory of Planned Behaviour: A meta-analytic review. British Journal of Social Psychology, 40(4), 471–499. https://doi.org/10.1348/014466601164939

Asendorpf, J. B., & Wilpers, S. (1998). Personality effects on social relationships. Journal of Personality and Social Psychology, 74(6), 1531–1544. https://doi.org/10.1037/0022-3514.74.6.1531

Ashby, W. R. (1991). Requisite Variety and Its Implications for the Control of Complex Systems. In G. J. Klir, Facets of Systems Science (pp. 405–417). https://doi.org/10.1007/978-1-4899-0718-9_28

Avruch, K. (1998). Culture and Conflict Resolution. Washington, D.C.: United States Institute of Peace Press.

Ayres, R., & Ayres, L. (2002). A Handbook of Industrial Ecology. https://doi.org/10.4337/9781843765479

Bada, & Olusegun, S. (2015). Constructivism Learning Theory: A Paradigm for Teaching and Learning.

Baghramian, M., & Carter, J. A. (2018). Relativism. In E. N. Zalta (Ed.), The Stanford Encyclopedia of Philosophy (Winter 2018). Retrieved from https://plato.stanford.edu/archives/win2018/entries/relativism/

Bale, C. S. E., Varga, L., & Foxon, T. J. (2015). Energy and complexity: New ways forward. Applied Energy, 138, 150–159. https://doi.org/10.1016/j.apenergy.2014.10.057

Ball-Rokeach, S. J. (1985). The origins of individual media-system dependency: A sociological framework. Communication Research, 12(4), 485–510.

Ball-Rokeach, S. J., & DeFleur, M. L. (1976). A Dependency Model Of Mass-Media Effects. Communication Research, 3(1), 3–21.

Balta-Ozkan, N., Yildirim, J., & Connor, P. M. (2015). Regional distribution of photovoltaic deployment in the UK and its determinants: A spatial econometric approach. Energy Economics, 51, 417–429. https://doi.org/10.1016/j.eneco.2015.08.003

Bardi, A., & Schwartz, S. H. (2003). Values and Behavior: Strength and Structure of Relations. Personality and Social Psychology Bulletin, 29(10), 1207–1220. https://doi.org/10.1177/0146167203254602

Barendrecht, J. M., Harchaoui, S., Omlo, J. J., el Baktit, F. A., & de Ruiter, D. (2009). Polariseren binnen onze grenzen. Retrieved from https://www.scp.nl/Publicaties/Alle_publicaties/Publicaties_2019/Burgerperspectieven_2019_1

Barton, A. H., & Parsons, R. W. (1977). Measuring Belief System Structure. Public Opinion Quarterly, 41(2), 159. https://doi.org/10.1086/268372

Baumeister, R. F., & Masicampo, E. J. (2010). Conscious thought is for facilitating social and cultural interactions: How mental simulations serve the animal–culture interface. Psychological Review, 117(3), 945–971. https://doi.org/10.1037/a0019393

Becker, J., Brackbill, D., & Centola, D. (2017). Network dynamics of social influence in the wisdom of crowds. Proceedings of the National Academy of Sciences, 201615978. https://doi.org/10.1073/pnas.1615978114

Bergman, M. M. (1998). A Theoretical Note on the Differences Between Attitudes, Opinions, and Values. Swiss Political Science Review, 4(2), 81–93. https://doi.org/10.1002/j.1662-6370.1998.tb00239.x

Bodur, H. O., Brinberg, D., & Coupey, E. (2000). Belief, affect, and attitude: Alternative models of the determinant of attitude. Journal of Consumer Psychology, 17–28.

Bohner, G., & Dickel, N. (2011). Attitudes and Attitude Change. Annual Review of Psychology, 62(1), 391–417. https://doi.org/10.1146/annurev.psych.121208.131609

Bollinger, L. A., Davis, C. B., Evins, R., Chappin, E. J. L., & Nikolic, I. (2018). Multi-model ecologies for shaping future energy systems: Design patterns and development paths. Renewable and Sustainable Energy Reviews, 82, 3441–3451. https://doi.org/10.1016/j.rser.2017.10.047

Bollinger, L. A., Nikolić, I., Davis, C. B., & Dijkema, G. P. J. (2015). Multimodel Ecologies: Cultivating Model Ecosystems in Industrial Ecology: Multimodel Ecologies. Journal of Industrial Ecology, 19(2), 252–263. https://doi.org/10.1111/jiec.12253

Boogaard, B. K., Oosting, S. J., & Bock, B. B. (2006). Elements of societal perception of farm animal welfare: A quantitative study in The Netherlands. Livestock Science, 104(1–2), 13–22. https://doi.org/10.1016/j.livsci.2006.02.010

Borgatti, S. P., Mehra, A., Brass, D. J., & Labianca, G. (2009). Network Analysis in the Social Sciences. Science, 323(5916), 892–895.

Box, G. E. P. (1979). Some Problems of Statistics and Everyday Life. Journal of the American Statistical Association, 74(365), 1–4.

Boyd, R., & Richerson, P. J. (2009). Culture and the evolution of human cooperation. Philosophical Transactions of the Royal Society B: Biological Sciences, 364(1533), 3281–3288. https://doi.org/10.1098/rstb.2009.0134

Bozdag, E., & van den Hoven, J. (2015). Breaking the filter bubble: Democracy and design. Ethics and Information Technology, 17(4), 249–265. https://doi.org/10.1007/s10676-015-9380-y

Bray, J. P. (2008). Consumer Behaviour Theory: Approaches and Models. Retrieved from http://eprints.bournemouth.ac.uk/10107/

Brick, C., Sherman, D. K., & Kim, H. S. (2017). "Green to be seen" and "brown to keep down": Visibility moderates the effect of identity on pro-environmental behavior. Journal of Environmental Psychology, 51, 226–238. https://doi.org/10.1016/j.jenvp.2017.04.004

Brinkman, R. L., & Brinkman, J. E. (1997). Cultural lag: Conception and theory. International Journal of Social Economics, 24(6), 609–627. https://doi.org/10.1108/03068299710179026

Brousmiche, K.-L., Kant, J.-D., Sabouret, N., & Prenot-Guinard, F. (2016). From Beliefs to Attitudes: Polias, a Model of Attitude Dynamics Based on Cognitive Modeling and Field Data. Journal of Artificial Societies and Social Simulation, 19(4). https://doi.org/10.18564/jasss.3161

Burrus, J., & Carney, L. (2015). Social Beliefs and Attitudes: Personality and the Isms. In International Encyclopedia of the Social & Behavioral Sciences (pp. 162–167). https://doi.org/10.1016/B978-0-08-097086-8.25082-4

Byrka, K. (2009). Attitude-behavior consistency: Campbell's paradigm in environmental and health domains (Technische Universiteit Eindhoven). https://doi.org/10.6100/ir642840

Cacioppo, J. T., Petty, R. E., Feinstein, J. A., & Jarvis, W. B. G. (1996). Dispositional Differences in Cognitive Motivation: The Life and Times of Individuals Varying in Need for Cognition. Psychological Bulletin, 119(2), 197–253.

Calder, M., Craig, C., Culley, D., Cani, R. de, Donnelly, C. A., Douglas, R., ... Wilson, A. (2018). Computational modelling for decision-making: Where, why, what, who and how. Open Science, 5(6), 172096. https://doi.org/10.1098/rsos.172096

Centola, D. (2015). The Social Origins of Networks and Diffusion. American Journal of Sociology, 120(5), 1295–1338. https://doi.org/10.1086/681275

Centola, D., Gonzalez-Avella, J. C., Eguiluz, V. M., & Miguel, M. S. (2007). Homophily, Cultural Drift and the Co-Evolution of Cultural Groups. Journal of Conflict Resolution, 51(6), 905–929. https://doi.org/10.1177/0022002707307632

Chai, S.-K. (2009). The Coherence Model of Preference and Belief Formation. In Social Computing and Behavioral Modeling (pp. 1–9). https://doi.org/10.1007/978-1-4419-0056-2_10

Chappin, E. J. L. (2011). Simulating Energy Transitions (TU Delft). Retrieved from http://chappin.com/ChappinEJL-PhDthesis.pdf

Chen, S., & Chaiken, S. (1999). The heuristic-systematic model in its broader context. In Dual-process theories in social psychology (Vol. 15, pp. 73–96). New York, NY, USA: The Guilford Press.

Cheng, J. T., Tracy, J. L., & Henrich, J. (2010). Pride, personality, and the evolutionary foundations of human social status. Evolution and Human Behavior, 31(5), 334–347. https://doi.org/10.1016/j.evolhumbehav.2010.02.004

Çileli, M. (2000). Change in Value Orientations of Turkish Youth From 1989 to 1995. The Journal of Psychology, 134(3), 297–305. https://doi.org/10.1080/00223980009600869

Claudy, M. C., Peterson, M., & O'Driscoll, A. (2013). Understanding the Attitude-Behavior Gap for Renewable Energy Systems Using Behavioral Reasoning Theory. Journal of Macromarketing, 33(4), 273–287. https://doi.org/10.1177/0276146713481605

Cook, J., Nuccitelli, D., Green, S. A., Richardson, M., Winkler, B., Painting, R., ... Skuce, A. (2013). Quantifying the consensus on anthropogenic global warming in the scientific literature. Environmental Research Letters, 8(2), 024024. https://doi.org/10.1088/1748-9326/8/2/024024

Courtenay-Hall, P., & Rogers, L. (2002). Gaps in Mind: Problems in environmental knowledge-behaviour modelling research. Environmental Education Research, 8(3), 283–297. https://doi.org/10.1080/13504620220145438

Critchley, H. D., & Garfinkel, S. N. (2018). The influence of physiological signals on cognition. Current Opinion in Behavioral Sciences, 19, 13–18. https://doi.org/10.1016/j.cobeha.2017.08.014

Dandekar, P., Goel, A., & Lee, D. T. (2013). Biased assimilation, homophily, and the dynamics of polarization. Proceedings of the National Academy of Sciences, 110(15), 5791–5796. https://doi.org/10.1073/pnas.1217220110

Davis, T., Hennes, E. P., & Raymond, L. (2018). Cultural evolution of normative motivations for sustainable behaviour. Nature Sustainability, 1(5), 218–224. https://doi.org/10.1038/s41893-018-0061-9

de Wildt, T. (2017). Modeling Values Attributed to Smart Energy Systems. ACM. https://doi.org/DOI: 10.475/123_4

de Witt, A. (2018). Transformative Solutions for Sustainable Well-Being. In Handbook of Engaged Sustainability. Retrieved from https://www.researchgate.net/publication/325740500

Dekker, P., & den Ridder, J. (2019). Burgerperspectieven 2019|1 (p. 51). Den Haag: Sociaal en Cultureel Planbureau.

Demski, C., Butler, C., Parkhill, K. A., Spence, A., & Pidgeon, N. F. (2015a). Public values for energy system change. Global Environmental Change, 34, 59–69. https://doi.org/10.1016/j.gloenvcha.2015.06.014

Demski, C., Butler, C., Parkhill, K. A., Spence, A., & Pidgeon, N. F. (2015b). Public values for energy system change. Global Environmental Change, 34, 59–69. https://doi.org/10.1016/j.gloenvcha.2015.06.014

Dietz, T., Fitzgerald, A., & Shwom, R. (2005). Environmental Values. Annual Review of Environment and Resources, 30(1), 335–372. https://doi.org/10.1146/annurev.energy.30.050504.144444

Dignum, F., Dignum, V., & Jonker, C. (2008). Towards agents for policy making. In Multi-Agent-Based Simulation IX (pp. 141–153). Berlin, Heidelberg: Springer.

Dimulescu, A., & Dessalles, J.-L. (2009). Understanding Narrative Interest: Some Evidence on the Role of Unexpectedness. Proceedings of the Annual Meeting of the Cognitive Science Society, 31(31), 7.

Dopfer, K., Foster, J., & Potts, J. (2004). Micro-meso-macro. Journal of Evolutionary Economics, 14(3), 263–279. https://doi.org/10.1007/s00191-004-0193-0

Dorian, J. P., Franssen, H. T., & Simbeck, D. R. (2006). Global challenges in energy. Energy Policy, 34(15), 1984–1991. https://doi.org/10.1016/j.enpol.2005.03.010

Dunning, D., Griffin, D. W., Milojkovic, J. D., & Ross, L. (1990). The Overconfidence Effect in Social Prediction. Journal of Personality and Social Psychology, 58(4), 14.

Edmonds, B. (2010). Bootstrapping Knowledge About Social Phenomena Using Simulation Models. Journal of Artificial Societies and Social Simulation, 13(1), 8. https://doi.org/10.18564/jasss.1523

Edmonds, B, & Moss, S. (2005). Towards Good Social Science. Journal of Artificial Societies and Social Simulation, 8(4). Retrieved from http://jasss.soc.surrey.ac.uk/8/4/13.html

Edmonds, Bruce, Grimm, V., Meyer, R., Montañola, C., Ormerod, P., Root, H., & Squazzoni, F. (2019). Different Modelling Purposes. Journal of Artificial Societies and Social Simulation, 22(3), 30. https://doi.org/10.18564/jasss.3993 Url: http://jasss.soc.surrey.ac.uk/22/3/6.html

Ehrenfeld, J. R. (2004). Searching for Sustainability. Reflections, 5(8), 1–13.

Emmons, R. A. (1989). Exploring the Relations Between Motives and Traits: The Case of Narcissism. In Personality Psychology (pp. 32–44). New York, NY, USA: Springer.

Energysage. (2019a). Pros and Cons of Electric Cars. Retrieved July 10, 2019, from Pros and Cons of Electric Cars website: https://www.energysage.com/electric-vehicles/101/pros-and-cons-electric-cars/

Energysage. (2019b, May 2). Pros and Cons of Solar Energy. Retrieved July 10, 2019, from Solar News website: https://news.energysage.com/advantages-and-disadvantages-of-solar-energy/

Epstein, J. M. (1999). Agent-based computational models and generative social science. Complexity, 4(5), 41–60.

Epstein, J. M. (2008). Why Model? Journal of Artificial Societies and Social Simulation, 11(4), 12.

Evans, J. (2008). Dual-Processing Accounts of Reasoning, Judgment, and Social Cognition. Annual Review of Psychology, 59(1), 255–278. https://doi.org/10.1146/annurev.psych.59.103006.093629

Fazio, R. H. (2007). Attitudes as Object-Evaluation Associations of Varying Strength. Social Cognition, 25(5), 603–637. https://doi.org/10.1521/soco.2007.25.5.603

Ferraro, G. P. (2002). The cultural dimension of international business (4th ed). Upper Saddle River, NJ: Prentice Hall.

Fershtman, C., Gneezy, U., & Hoffman, M. (2011). Taboos and Identity: Considering the Unthinkable. American Economic Journal: Microeconomics, 3(2), 139–164. https://doi.org/10.1257/mic.3.2.139

Feygina, I., Jost, J. T., & Goldsmith, R. E. (2010). System Justification, the Denial of Global Warming, and the Possibility of "System-Sanctioned Change." Personality and Social Psychology Bulletin, 36(3), 326–338. https://doi.org/10.1177/0146167209351435

Fishbein, M., & Ajzen, I. (1975). Belief, attitude, intention and behaviour: An introduction to theory and research. Reading, Massachusetts: Addison-Wesley.

Flache, A. (2018). Between Monoculture and Cultural Polarization: Agent-based Models of the Interplay of Social Influence and Cultural Diversity. Journal of Archaeological Method and Theory, 25(4), 996–1023. https://doi.org/10.1007/s10816-018-9391-1

Flache, A., & Macy, M. W. (2011). Local Convergence and Global Diversity: From Interpersonal to Social Influence. Journal of Conflict Resolution, 55(6), 970–995. https://doi.org/10.1177/0022002711414371

Flache, A., Mäs, M., Feliciani, T., Chattoe-Brown, E., Deffuant, G., Huet, S., & Lorenz, J. (2017). Models of Social Influence: Towards the Next Frontiers. Journal of Artificial Societies and Social Simulation, 20(4). https://doi.org/10.18564/jasss.3521

Flynn, R., Bellaby, P., & Ricci, M. (2009). The 'Value-Action Gap' in Public Attitudes towards Sustainable Energy: The Case of Hydrogen Energy. The Sociological Review, 57(2_suppl), 159–180. https://doi.org/10.1111/j.1467-954X.2010.01891.x

Fornara, F., Pattitoni, P., Mura, M., & Strazzera, E. (2016). Predicting intention to improve household energy efficiency: The role of value-belief-norm theory, normative and informational influence, and specific attitude. Journal of Environmental Psychology, 45, 1–10. https://doi.org/10.1016/j.jenvp.2015.11.001

Foss, N. J. (2000). The Dangers and Attractions of Theoretical Eclecticism. Journal of Macromarketing, 20(1), 65–67. https://doi.org/10.1177/0276146700201007

Frederick, S., & Loewenstein, G. (2002). Time Discounting and Time Preference: A Critical Review. Journal of Economic Literature, 40(2), 351–401.

Frederiks, E. R., Stenner, K., & Hobman, E. V. (2015). Household energy use: Applying behavioural economics to understand consumer decision-making and behaviour. Renewable and Sustainable Energy Reviews, 41, 1385–1394. https://doi.org/10.1016/j.rser.2014.09.026

Frenken, K. (2006). Technological innovation and complexity theory. Economics of Innovation and New Technology, 15(2), 137–155. https://doi.org/10.1080/10438590500141453

Friedkin, N.E., & Johnsen, E. C. (1990). Social influence networks and opinion change. Journal of Mathematical Sociology, 15(3–4), 193–206.

Friedkin, Noah E., Proskurnikov, A. V., Tempo, R., & Parsegov, S. E. (2016). Network science on belief system dynamics under logic constraints. Science, 354(6310), 321–326. https://doi.org/10.1126/science.aag2624

Galán, J. M., Izquierdo, L. R., Izquierdo, S. S., Santos, J. I., del Olmo, R., López-Paredes, A., & Edmonds, B. (2009). Errors and Artefacts in Agent-Based Modelling. Journal of Artificial Societies and Social Simulation, 12(1). Retrieved from http://jasss.soc.surrey.ac.uk/12/1/1.html

Gärdenfors, P. (2005). The Dynamics of Belief Systems: Foundations vs. Coherence Theories. In The Dynamics of Thought (pp. 47–65). https://doi.org/10.1007/1-4020-3399-0_4

Geels, F. W., Sovacool, B. K., Schwanen, T., & Sorrell, S. (2017). The Socio-Technical Dynamics of Low-Carbon Transitions. Joule, 1(3), 463–479. https://doi.org/10.1016/j.joule.2017.09.018

Geels, Frank W. (2002). Technological transitions as evolutionary reconfiguration processes: A multi-level perspective and a case-study. Research Policy, 31(8–9), 1257–1274. https://doi.org/10.1016/S0048-7333(02)00062-8

Gelfand, M. J., & Jackson, J. C. (2016). From one mind to many: The emerging science of cultural norms. Current Opinion in Psychology, 8, 175–181. https://doi.org/10.1016/j.copsyc.2015.11.002

Gerbner, G. (1998). Cultivation analysis: An overview. Mass Communication and Society, 1(3/4), 175–194.

Gerbner, G., Gross, L., Morgan, M., & Signorielli, N. (1986). Living with Television: The Dynamics of the Cultivation Process. Perspectives on Media Effects, 17–40.

Gilbert, N., & Terna, P. (2000). How to build and use agent-based models in social science. Mind & Society, 1(1), 57–72. https://doi.org/10.1007/BF02512229

Goldsmith, M., & Thomas, R. R. (2003). Understanding Referent Groups and Diversity. In Human Resources in the 21st Century (pp. 51–56). Hoboken, NJ: John Wiley & Sons, Inc.

Gotts, N. M., & Polhill, J. G. (2017). Experiments with a Model of Domestic Energy Demand. Journal of Artificial Societies and Social Simulation, 20(3). https://doi.org/10.18564/jasss.3467

Gowdy, J. M. (1994). The Social Context of Natural Capital: The Social Limits to Sustainable Development. International Journal of Social Economics, 21(8), 43–55. https://doi.org/10.1108/03068299410065412

Graham, J., Haidt, J., & Nosek, B. A. (2009). Liberals and conservatives rely on different sets of moral foundations. Journal of Personality and Social Psychology, 96(5), 1029–1046. https://doi.org/10.1037/a0015141

Grewal, R., Mehta, R., & Kardes, F. R. (2000). The role of the social-identity function of attitudes in consumer innovativeness and opinion leadership. Journal of Economic Psychology, 21(3), 233–252. https://doi.org/10.1016/S0167-4870(00)00003-9

Grube, J. W., Mayton, D. M., & Ball-Rokeach, S. J. (1994). Inducing Change in Values, Attitudes, and Behaviors: Belief System Theory and the Method of Value Self-Confrontation. Journal of Social Issues, 50(4), 153–173. https://doi.org/10.1111/j.1540-4560.1994.tb01202.x

Grube, J. W., Mayton, D. M., & Ball-Rokeach, S. J. (1994). Inducing Change in Values, Attitudes, and Behaviors: Belief System Theory and the Method of Value Self-Confrontation. Journal of Social Issues, 50(4), 153–173. https://spssi-onlinelibrary-wiley-com.tudelft.idm.oclc.org/doi/abs/10.1111/j.1540-4560.1994.tb01202.x

Gupta, D. K., Langelaar, M., Barink, M., & van Keulen, F. (2016). Optimizing front metallization patterns: Efficiency with aesthetics in free-form solar cells. Renewable Energy, 86, 1332–1339. https://doi.org/10.1016/j.renene.2015.09.071

Haidt, J. (2012). The righteous mind: Why good people are divided by politics and religion. Retrieved from https://psycnet.apa.org/record/2011-29583-000
Haidt, J., & Bjorklund, F. (2007). Social Intuitionists Answer Six Questions about Moral Psychology. In W. Sinnott-Armstrong, Moral Psychology (Vol. 2). https://doi.org/10.7551/mitpress/7573.003.0006
Hansen, T. (2008). Consumer values, the theory of planned behaviour and online grocery shopping. International Journal of Consumer Studies, 32(2), 128–137. https://doi.org/10.1111/j.1470-6431.2007.00655.x
Harmon-Jones, E., Amodio, D. M., & Harmon-Jones, C. (2009). Action-based model of dissonance: A review, integration, and expansion of conceptions of cognitive conflict. In Advances in Experimental Social Psychology (Vol. 41, pp. 119–166). https://doi.org/10.1016/S0065-2601(08)00403-6
Harmon-Jones, E., & Harmon-Jones, C. (2007). Cognitive Dissonance Theory After 50 Years of Development. Zeitschrift Für Sozialpsychologie, 38(1), 7–16. https://doi.org/10.1024/0044-3514.38.1.7
Harris, J. M., & Roach, B. (2017). Environmental and natural resource economics: A contemporary approach (4th Edition). New York: Routledge.
Hassan, S., Antunes, L., & Arroyo, M. (2009). Deepening the Demographic Mechanisms in a Data-Driven Social Simulation of Moral Values Evolution. In N. David & J. S. Sichman (Eds.), Multi-Agent-Based Simulation IX (Vol. 5269, pp. 167–182). https://doi.org/10.1007/978-3-642-01991-3_13
Hatfield, E., Cacioppo, J. T., & Rapson, R. L. (1993). Emotional Contagion. Current Directions in Psychological Science, 2(3), 96–100.
Healy, A., & Malhotra, N. (2013). Childhood Socialization and Political Attitudes: Evidence from a Natural Experiment. The Journal of Politics, 75(4), 1023–1037. https://doi.org/10.1017/S0022381613000996
Heath, R. L., & Gay, C. D. (1997). Risk Communication: Involvement, Uncertainty, and Control's Effect on Information Scanning and Monitoring by Expert Stakeholders. Management Communication Quarterly, 10(3), 342–372. https://doi-org.tudelft.idm.oclc.org/10.1177%2F0893318997010003004
Heins, V. (2007). Critical theory and the traps of conspiracy thinking. Philosophy & Social Criticism, 33(7), 787–801. https://doi.org/10.1177/0191453707081675
Hessing-Couvret, E., & Reuling, A. (2002). Het WIN-model^{TM}, Waardensegmenten in Nederland. Amsterdam: TNS NIPO.
Hills, M. D. (2002). Kluckhohn and Strodtbeck's Values Orientation Theory. Online Readings in Psychology and Culture, 4(4). https://doi.org/10.9707/2307-0919.1040
Hitlin, S., & Piliavin, J. A. (2004). Values: Reviving a Dormant Concept. Annual Review of Sociology, 30(1), 359–393. https://doi.org/10.1146/annurev.soc.30.012703.110640
Hogg, M. A. (2007). Uncertainty–identity theory. Advances in Experimental Social Psychology, 39, 69–126.
Holling, C. S. (2001). Understanding the Complexity of Economic, Ecological, and Social Systems. Ecosystems, 4(5), 390–405. https://doi.org/10.1007/s10021-001-0101-5
Homer, P. M., & Kahle, L. R. (1988). A structural equation test of the value-attitude-behavior hierarchy. Journal of Personality and Social Psychology, 54(4). Retrieved from http://web.csulb.edu/~pamela/pubs/Value_Attitude_Hierarchy.pdf
Homer-Dixon, T., Maynard, J. L., Mildenberger, M., Milkoreit, M., Mock, S. J., Quilley, S., … Thagard, P. (2013). A Complex Systems Approach to the Study of Ideology: Cognitive-Affective Structures and the Dynamics of Belief Systems. Journal of Social and Political Psychology, 1(1), 337–363. https://doi.org/10.5964/jspp.v1i1.36

Horcajo, J., Petty, R. E., & Briñol, P. (2010). The effects of majority versus minority source status on persuasion: A self-validation analysis. Journal of Personality and Social Psychology, 99(3), 498–512. https://doi.org/10.1037/a0018626

Hornsey, M. J. (2008). Social Identity Theory and Self-categorization Theory: A Historical Review. Social and Personality Psychology Compass, 2(1), 204–222. https://doi.org/10.1111/j.1751-9004.2007.00066.x

Howard, J. A., & Sheth, J. N. (1969). The Theory of Buyer Behavior. New York, NY, US: John Wiley & Sons, Inc.

Inglehart, R., & Baker, W. E. (2000). Modernization, Cultural Change, and the Persistence of Traditional Values. American Sociological Review, 65(1), 19–51. https://doi.org/10.2307/2657288

Intergovernmental Panel on Climate Change. (2015). Climate Change 2014: A Synthesis Report. Geneva, Switzerland.

Iooss, B., & Saltelli, A. (2017). Introduction to Sensitivity Analysis. In R. Ghanem, D. Higdon, & H. Owhadi (Eds.), Handbook of Uncertainty Quantification (pp. 1103–1122). https://doi.org/10.1007/978-3-319-12385-1_31

IRENA. (2012). Renewable Energy Technologies—Cost Analysis Series: Solar Photovoltaics. (No. 4/5; p. 45). Retrieved from International Renewable Energy Agency website: www.irena.org/Publications

Iyengar, S., & Hahn, K. S. (2009). Red Media, Blue Media: Evidence of Ideological Selectivity in Media Use. Journal of Communication, 59(1), 19–39. https://doi.org/10.1111/j.1460-2466.2008.01402.x

Jackob, N. G. E. (2010). No Alternatives? The Relationship between Perceived Media Dependency, Use of Alternative Information Sources, and General Trust in Mass Media. International Journal of Communication, 4, 18.

Jager, W. (2017). Enhancing the Realism of Simulation (EROS): On Implementing and Developing Psychological Theory in Social Simulation. Journal of Artificial Societies and Social Simulation, 20(3). https://doi.org/10.18564/jasss.3522

Jager, W., & Amblard, F. (2005). Uniformity, Bipolarization and Pluriformity Captured as Generic Stylized Behavior with an Agent-Based Simulation Model of Attitude Change. Computational & Mathematical Organization Theory, 10(4), 295–303. https://doi.org/10.1007/s10588-005-6282-2

Jones, N. A., Shaw, S., Ross, H., Witt, K., & Pinner, B. (2016). The study of human values in understanding and managing social-ecological systems. Ecology and Society, 21(1). https://doi.org/10.5751/ES-07977-210115

Kahan, D. M. (2016). The Politically Motivated Reasoning Paradigm, Part 1: What Politically Motivated Reasoning Is and How to Measure It. In R. A. Scott & S. M. Kosslyn (Eds.), Emerging Trends in the Social and Behavioral Sciences (pp. 1–16). https://doi.org/10.1002/9781118900772.etrds0417

Kemp, R. (2010). The Dutch energy transition approach. International Economics and Economic Policy, 7(2–3), 291–316. https://doi.org/10.1007/s10368-010-0163-y

Kennedy, E. H., Beckley, T. M., McFarlane, B. L., & Nadeau, S. (2009). Why We Don't "Walk the Talk": Understanding the Environmental Values/Behaviour Gap in Canada. Human Ecology Review, 16(2), 10.

Kiesling, E., Günther, M., Stummer, C., & Wakolbinger, L. M. (2012). Agent-based simulation of innovation diffusion: A review. Central European Journal of Operations Research, 20(2), 183–230. https://doi.org/10.1007/s10100-011-0210-y

Kilby, R. W. (1993). The Study of Human Values. Lanham, Md: University Press of America.

Kim, Y., Hsu, S.-H., & de Zúñiga, H. G. (2013). Influence of Social Media Use on Discussion Network Heterogeneity and Civic Engagement: The Moderating Role of Personality Traits: Social Media & Personality Traits. Journal of Communication, 63(3), 498–516. https://doi.org/10.1111/jcom.12034

Kinzig, A. P., Ehrlich, P. R., Alston, L. J., Arrow, K., Barrett, S., Buchman, T. G., ... Saari, D. (2013). Social Norms and Global Environmental Challenges: The Complex Interaction of Behaviors, Values, and Policy. BioScience, 63(3), 164–175. https://doi.org/10.1525/bio.2013.63.3.5

Klein, G., Moon, B., & Hoffman, R. R. (2006). Making Sense of Sensemaking 1: Alternative Perspectives. IEEE Intelligent Systems, 21(4), 70–73. https://doi.org/10.1109/MIS.2006.75

Kluckhohn, C. (1962). Values and value-orientations in the theory of action: An exploration in definition and classification. In T. Parsons & E. Shils, Toward a general theory of action (pp. 388–433). Cambridge, Massachusetts: Harvard University Press.

Köhler, J., de Haan, F., Holtz, G., Kubeczko, K., Moallemi, E., Papachristos, G., & Chappin, E. (2018). Modelling Sustainability Transitions: An Assessment of Approaches and Challenges. Journal of Artificial Societies and Social Simulation, 21(1). https://doi.org/10.18564/jasss.3629

Koops, B.-J., Newell, B. C., Timan, T., Chokrevski, T., & Gali, M. (2017). A Typology of Privacy. 38, 93.

Kostrova, E. (2018). The "Ought"-Dimension in Value Theory: The Concept of the Desirable in John Dewey's Definition of Value and Its Significance for the Social Sciences. In A. Christian, D. Hommen, N. Retzlaff, & G. Schurz (Eds.), Philosophy of Science: Between the Natural Sciences, the Social Sciences, and the Humanities (pp. 171–185). https://doi.org/10.1007/978-3-319-72577-2_10

Kramer, M. W. (2016). Sensemaking. In The International Encyclopedia of Organizational Communication (pp. 1–10). https://doi.org/10.1002/9781118955567.wbieoc185

Krebs, F. (2017). An Empirically Grounded Model of Green Electricity Adoption in Germany: Calibration, Validation and Insights into Patterns of Diffusion. Journal of Artificial Societies and Social Simulation, 20(2), 24.

Künneke, R., Mehos, D. C., Hillerbrand, R., & Hemmes, K. (2015). Understanding values embedded in offshore wind energy systems: Toward a purposeful institutional and technological design. Environmental Science & Policy, 53, 118–129. https://doi.org/10.1016/j.envsci.2015.06.013

Lachlan, K. A., Spence, P. R., & Seeger, M. (2009). Terrorist attacks and uncertainty reduction: Media use after September 11. Behavioral Sciences of Terrorism and Political Aggression, 1(2), 101–110. https://doi.org/10.1080/19434470902771683

Langner, S., Hennigs, N., & Wiedmann, K.-P. (2013). Social persuasion: Targeting social identities through social influencers. Journal of Consumer Marketing, 30(1), 31–49. https://doi.org/10.1108/07363761311290821

Lashof, D. A., & Ahuja, D. R. (1990). Relative contributions of greenhouse gas emissions to global warming. 344. Retrieved from http://www.nature.com.tudelft.idm.oclc.org/articles/344529a0.pdf

Lazer, D. M. J., Baum, M. A., Benkler, Y., Berinsky, A. J., Greenhill, K. M., Menczer, F., ... Zittrain, J. L. (2018). The science of fake news. Science, 359(6380), 1094–1096. https://doi.org/10.1126/science.aao2998

Le Treut, H., Somerville, R., Cubasch, U., Ding, Y., Mauritzen, A., Mokssit, A., ... Prather, M. (2007). Historical Overview of Climate Change Science (p. 36). Cambridge, United Kingdom: Cambridge University Press.

Leiserowitz, A. A., Kates, R. W., & Parris, T. M. (2006). Sustainability Values, Attitudes, and Behaviors: A Review of Multinational and Global Trends. Annual Review of Environment and Resources, 31(1), 413–444. https://doi.org/10.1146/annurev.energy.31.102505.133552

Lemaine, G. (1974). Social differentiation and social originality. European Journal of Social Psychology, 4(1), 17–52. https://doi.org/10.1002/ejsp.2420040103

Lempert, R. J., Popper, S. W., & Bankes, S. C. (2003). Shaping the next one hundred years: New methods for quantitative, long-term policy analysis. Santa Monica, CA: RAND.
Leonardelli, G. J., Pickett, C. L., & Brewer, M. B. (2010). Optimal Distinctiveness Theory. In Advances in Experimental Social Psychology (Vol. 43, pp. 63–113). https://doi.org/10.1016/S0065-2601(10)43002-6
Levine, R. L. (2003). Models of Attitude and Belief Change from the Perspective of System Dynamics. In Proceedings of the 2003 International System Dynamics Conference. Presented at the New York, NY, USA. New York, NY, USA: The System Dynamics Society.
Lewis, J. D., & Weigert, A. (1985). Trust as a Social Reality. Social Forces, 63(4), 967–985.
Li, X., Mao, W., Zeng, D., & Wang, F.-Y. (2008). Agent-Based Social Simulation and Modeling in Social Computing. In C. C. Yang, H. Chen, M. Chau, K. Chang, S.-D. Lang, P. S. Chen, … J. Zhan (Eds.), Intelligence and Security Informatics (Vol. 5075, pp. 401–412). https://doi.org/10.1007/978-3-540-69304-8_41
Ligmann-Zielinska, A., Kramer, D. B., Spence Cheruvelil, K., & Soranno, P. A. (2014). Using Uncertainty and Sensitivity Analyses in Socioecological Agent-Based Models to Improve Their Analytical Performance and Policy Relevance. PLoS ONE, 9(10), e109779. https://doi.org/10.1371/journal.pone.0109779
Ligmann-Zielinska, A., & Sun, L. (2010). Applying time-dependent variance-based global sensitivity analysis to represent the dynamics of an agent-based model of land use change. International Journal of Geographical Information Science, 24(12), 1829–1850. https://doi.org/10.1080/13658816.2010.490533
Liljenström, H., & Svedin, U. (2005). Micro, meso, macro: Addressing complex systems couplings. Retrieved from https://www.researchgate.net/publication/310674882_Micro_meso_macro_Addressing_complex_systems_couplings
Lorenz, J. (2007). Continuous Opinion Dynamics under Bounded Confidence: A Survey. International Journal of Modern Physics C, 18(12), 1819–1838. https://doi.org/10.1142/S0129183107011789
Lorscheid, I., Heine, B.-O., & Meyer, M. (2012). Opening the 'black box' of simulations: Increased transparency and effective communication through the systematic design of experiments. Computational and Mathematical Organization Theory, 18(1), 22–62. https://doi.org/10.1007/s10588-011-9097-3
Lustig, M. W., & Koester, J. (2010). Intercultural competence: Interpersonal communication across cultures (6th ed). Boston: Allyn & Bacon.
Mai, G. R., & Olson, J. M. (2000). Why we evaluate: Functions of attitudes. New Jersey, US: Lawrence Erlbaum Associates Publishers.
Maréchal, K. (2010). Not irrational but habitual: The importance of "behavioural lock-in" in energy consumption. Ecological Economics, 69(5), 1104–1114. https://doi.org/10.1016/j.ecolecon.2009.12.004
Mason, W. A., Conrey, F. R., & Smith, E. R. (2007). Situating Social Influence Processes: Dynamic, Multidirectional Flows of Influence Within Social Networks. Personality and Social Psychology Review, 11(3), 279–300. https://doi.org/10.1177/1088868307301032
Matsumoto, D., & Juang, L. (2016). Culture and Psychology (6th ed.). Retrieved from http://beet.the-eye.eu/public/WorldTracker.org/Sociology/Matsumoto%20-%20Culture%20and%20Psychology.pdf
Matutinović, I. (2007a). An Institutional Approach to Sustainability: Historical Interplay of Worldviews, Institutions and Technology. Journal of Economic Issues, 41(4), 1109–1137. https://doi.org/10.1080/00213624.2007.11507089
Matutinović, I. (2007b). Worldviews, institutions and sustainability: An introduction to a co-evolutionary perspective. International Journal of Sustainable

Development & World Ecology, 14(1), 92–102. https://doi.org/10.1080/13504500709469710
McDonald, R. I., & Crandall, C. S. (2015). Social norms and social influence. Current Opinion in Behavioral Sciences, 3, 147–151. https://doi.org/10.1016/j.cobeha.2015.04.006
McPherson, M., Smith-Lovin, L., & Cook, J. M. (2001). Birds of a Feather: Homophily in Social Networks. Annual Review of Sociology, 27(1), 415–444. https://doi.org/10.1146/annurev.soc.27.1.415
Meadows, D. (1997). Leverage points: Places to Intervene in a System. Whole Earth, 91(1), 78–84.
Meadows, M., & Cliff, D. (2012). Reexamining the Relative Agreement Model of Opinion Dynamics. Journal of Artificial Societies and Social Simulation, 15(4), 4. https://doi.org/10.18564/jasss.2083
Merriam-Webster. (2019a). Definition of Cultural Drift [Dictionary]. Retrieved October 8, 2019, from Merriam-webster.com website: https://www.merriam-webster.com/dictionary/cultural+drift
Merriam-Webster. (2019b). Medical Definition of Weber-Fechner Law [Dictionary]. Retrieved July 30, 2019, from Merriam-webster.com website: https://www.merriam-webster.com/medical/Weber-Fechner+law
Metcalf, S., & Paich, M. (2005, July 19). Spatial Dynamics of Social Network Evolution. 13.
Mittal, S., Diallo, S., Tolk, A., & Rouse, W. B. (2018). Emergent Behavior in Complex Systems Engineering: A Modeling and Simulation Approach. New Jersey, US: John Wiley & Sons, Inc.
Moglia, M., Cook, S., & McGregor, J. (2017). A review of Agent-Based Modelling of technology diffusion with special reference to residential energy efficiency. Sustainable Cities and Society, 31, 173–182. https://doi.org/10.1016/j.scs.2017.03.006
Moglia, M., Podkalicka, A., & McGregor, J. (2018). An Agent-Based Model of Residential Energy Efficiency Adoption. Journal of Artificial Societies & Social Simulation, 21(3), 26.
Mullainathan, S., & Shleifer, A. (2005). The Market for News. American Economic Review, 95(4), 1031–1053. https://doi.org/10.1257/0002828054825619
Nau, R. (2019). What's a good value for R-squared? Retrieved October 2, 2019, from Statistical forecasting: Notes on regression and time series analysis website: https://people.duke.edu/~rnau/rsquared.htm
Nikolic, I. (2009). Co-evolutionary method for modelling large scale socio-technical systems evolution. (Next Generation Infrastructures Foundation & TU Delft). Retrieved from https://repository.tudelft.nl/islandora/object/uuid%3Ab6855afa-e8ab-442d-ac5a-f645f7639c73
Nikolic, I. (2018). Heatmaster: Enabling Renewable Heat and Cold in Europe's Industrial Regions. Institute for Sustainable Process Technology.
Nordlund, A. (2009). Values, attitudes, and norms: Drivers in the Future Forests Context (p. 30). Retrieved from Umeå University website: https://www.slu.se/globalassets/ew/org/centrb/f-for/pdf/2009-nordlund-values-attitudes-and-norms.pdf
Norgaard, R. B. (1994). Development Betrayed. New York: Routledge.
Nutter, F. W., & Esker, P. D. (2006). The Role of Psychophysics in Phytopathology: The Weber–Fechner Law Revisited. European Journal of Plant Pathology, 114(2), 199–213. https://doi.org/10.1007/s10658-005-4732-9
Opschoor, J. B. (2003). Towards an Evolutionary Economic Approach to Sustainable Development. In V. FitzGerald (Ed.), Social Institutions and Economic Development (pp. 23–53). https://doi.org/10.1007/0-306-48159-6_3

Ostrom, T. M. (1988). Computer simulation: The third symbol system. Journal of Experimental Social Psychology, 24(5), 381–392. https://doi.org/10.1016/0022-1031(88)90027-3

Papadelis, S., & Flamos, A. (2019). An Application of Calibration and Uncertainty Quantification Techniques for Agent-Based Models. In H. Doukas, A. Flamos, & J. Lieu (Eds.), Understanding Risks and Uncertainties in Energy and Climate Policy: Multidisciplinary Methods and Tools for a Low Carbon Society. https://doi.org/10.1007/978-3-030-03152-7

Parsegov, S. E., Proskurnikov, A. V., Tempo, R., & Friedkin, N. E. (2017). Novel Multidimensional Models of Opinion Dynamics in Social Networks. IEEE Transactions on Automatic Control, 62(5), 2270–2285. https://doi.org/10.1109/TAC.2016.2613905

Pepper, M., Jackson, T., & Uzzell, D. (2009). An examination of the values that motivate socially conscious and frugal consumer behaviours. International Journal of Consumer Studies, 33(2), 126–136. https://doi.org/10.1111/j.1470-6431.2009.00753.x

Perlaviciute, G., & Steg, L. (2015). The influence of values on evaluations of energy alternatives. Renewable Energy, 77, 259–267. https://doi.org/10.1016/j.renene.2014.12.020

Petty, R.E., & Cacioppo, J. T. (1986). The elaboration likelihood model of persuasion. In Communication and persuasion (pp. 1–24). New York, NY, USA: Springer.

Petty, Richard E., Cacioppo, J. T., & Haugtvedt, C. P. (1992). Ego-Involvement and Persuasion: An Appreciative Look at the Sherif's Contribution to the Study of Self-Relevance and Attitude Change. In D. Granberg & G. Sarup (Eds.), Social Judgment and Intergroup Relations (pp. 147–174). https://doi.org/10.1007/978-1-4612-2860-8_7

Pfister, R., Schwarz, K. A., Janczyk, M., Dale, R., & Freeman, J. B. (2013). Good things peak in pairs: A note on the bimodality coefficient. Frontiers in Psychology, 4. https://doi.org/10.3389/fpsyg.2013.00700

Pianesi, F., Mana, N., Cappelletti, A., Lepri, B., & Zancanaro, M. (2008). Multimodal recognition of personality traits in social interactions. Proceedings of the 10th International Conference on Multimodal Interfaces - IMCI '08, 53. https://doi.org/10.1145/1452392.1452404

Piurko, Y., Schwartz, S. H., & Davidov, E. (2011). Basic Personal Values and the Meaning of Left-Right Political Orientations in 20 Countries. Political Psychology, 32(4), 537–561. https://doi.org/10.1111/j.1467-9221.2011.00828.x

Poortinga, W., Steg, L., & Vlek, C. (2004). Values, Environmental Concern, and Environmental Behavior: A Study into Household Energy Use. Environment and Behavior, 36(1), 70–93. https://doi.org/10.1177/0013916503251466

Prieur, C., & Tarantola, S. (2017). Variance-Based Sensitivity Analysis: Theory and Estimation Algorithms. In R. Ghanem, D. Higdon, & H. Owhadi (Eds.), Handbook of Uncertainty Quantification (pp. 1217–1239). https://doi.org/10.1007/978-3-319-12385-1_35

Quackenbush, R. L. (1989). Comparison and Contrast Between Belief System Theory and Cognitive Theory. The Journal of Psychology, 123(4), 315–328. https://doi.org/10.1080/00223980.1989.10542988

Rabinowicz, W., & Rønnow-Rasmussen, T. (2015). Value taxonomy. In Handbook of Value (pp. 23–42). Oxford: Oxford University Press.

Radil, S. M., Flint, C., & Tita, G. E. (2010). Spatializing Social Networks: Using Social Network Analysis to Investigate Geographies of Gang Rivalry, Territorially, and Violence in Los Angeles. Annals of the Association of American Geographers, 100(2), 307–326. Retrieved from JSTOR.

Rai, V., & Henry, A. D. (2016). Agent-based modelling of consumer energy choices. Nature Climate Change, 6(6), 556–562. https://doi.org/10.1038/nclimate2967

Rai, V., & Robinson, S. A. (2015). Agent-based modeling of energy technology adoption: Empirical integration of social, behavioral, economic, and environmental factors. Environmental Modelling & Software, 70, 163–177. https://doi.org/10.1016/j.envsoft.2015.04.014

Renewable Energy Hub. (2019). Heat Pumps Pros and Cons. Retrieved July 10, 2019, from The Renewable Energy Hub—A Complete Guide to Heat Pumps in 2019 website: https://www.renewableenergyhub.co.uk/main/heat-pumps-information/heat-pumps-pros-and-cons/

Rijksoverheid. (2017). Regeerakkoord 2017-2021 (p. 70). Retrieved from Rijksoverheid website: https://www.rijksoverheid.nl/documenten/publicaties/2017/10/10/regeerakkoord-2017-vertrouwen-in-de-toekomst

Robinson, S. A., & Rai, V. (2015). Determinants of spatio-temporal patterns of energy technology adoption: An agent-based modeling approach. Applied Energy, 151, 273–284. https://doi.org/10.1016/j.apenergy.2015.04.071

Roccas, S., Sagiv, L., Schwartz, S. H., & Knafo, A. (2002). The Big Five Personality Factors and Personal Values. Personality and Social Psychology Bulletin, 28(6), 789–801. https://doi.org/10.1177/0146167202289008

Rogers, E. M., Medina, U. E., Rivera, M. A., & Wiley, C. J. (2005). Complex Adaptive Systems and The Diffusion Of Innovations. The Innovation Journal: The Public Sector Innovation Journal, 10(3).

Rokeach, M. (1985). Inducing Change and Stability in Belief Systems and Personality Structures. Journal of Social Issues, 41(1), 153–171. https://doi.org/10.1111/j.1540-4560.1985.tb01123.x

Rokeach, M. (1994). A Theory of Organization and Change Within Value-Attitude Systems. Journal of Social Sciences, 24(1), 13–33.

Rokeach, M. (2008). Understanding Human Values. Simon and Schuster.

Roskos-Ewoldsen, B., Davies, J., & Roskos-Ewoldsen, D. R. (2004). Implications of the mental models approach for cultivation theory. Communications, 29(3). https://doi.org/10.1515/comm.2004.022

Rotmans, J., & Loorbach, D. (2009). Complexity and Transition Management. Journal of Industrial Ecology, 13(2), 184–196. https://doi.org/10.1111/j.1530-9290.2009.00116.x

Rozin, P., & Royzman, E. B. (2001). Negativity Bias, Negativity Dominance, and Contagion. Personality and Social Psychology Review, 5(4), 296–320. https://doi.org/10.1207/S15327957PSPR0504_2

RStudio. (2019). Open source and enterprise-ready professional software for data science—RStudio. Retrieved September 3, 2019, from https://www.rstudio.com/

Sagiv, L., & Schwartz, S. H. (2004). Values, intelligence and client behavior in career counseling: A field study. European Journal of Psychology of Education, 19(3), 237–254. https://doi.org/10.1007/BF03173222

Saltelli, A. (2002). Making best use of model evaluations to compute sensitivity indices. Computer Physics Communications, 145(2), 280–297. https://doi.org/10.1016/S0010-4655(02)00280-1

Salthe, S. N. (2007). What Is The Scope Of Biosemiotics? Information In Living Systems. In M. Barbieri (Ed.), Introduction to Biosemiotics (pp. 133–148). https://doi.org/10.1007/1-4020-4814-9_5

Schlegel, A. (2011). Human development and cultural transmission. Biological and Cultural Markers of Environmental Pressure, 68(4), 457–470.

Schnell, T. (2010). Existential Indifference: Another Quality of Meaning in Life. Journal of Humanistic Psychology, 50(3), 351–373. https://doi.org/10.1177/0022167809360259

Schröder, T., & Wolf, I. (2017). Modeling multi-level mechanisms of environmental attitudes and behaviours: The example of carsharing in Berlin. Journal of

Environmental Psychology, 52, 136–148. https://doi.org/10.1016/j.jenvp.2016.03.007
Schwartz, S. (2002). Value Priorities and Behavior: Applying a Theory of Integrated Value Systems. The Psychology of Values: The Ontario Symposium, 2(0), 119. https://doi.org/10.18682/pd.v2i0.514
Schwartz, S. H. (1994). Are There Universal Aspects in the Structure and Contents of Human Values? Journal of Social Issues, 50(4), 19–45. https://doi.org/10.1111/j.1540-4560.1994.tb01196.x
Schwartz, S. H. (2012). An Overview of the Schwartz Theory of Basic Values. Online Readings in Psychology and Culture, 2(1). https://doi.org/10.9707/2307-0919.1116
Schwartz, S. H., & Bilsky, W. (1987). Toward A Universal Psychological Structure of Human Values. Journal of Personality and Social Psychology, 53(3), 550–562. https://doi.org/10.1037//0022-3514.53.3.550
Schwarz, N., & Bohner, G. (2007). The Construction of Attitudes. In Abraham Tesser & N. Schwarz (Eds.), Blackwell Handbook of Social Psychology: Intraindividual Processes (pp. 436–457). https://doi.org/10.1002/9780470998519.ch20
Seligman, C., Olson, J. M., & Zanna, M. P. (Eds.). (1996). The psychology of values. Mahwah, N.J: L. Erlbaum Associates.
Shavitt, S., Lowrey, T. M., & Han, S.-P. (1992). Attitude functions in advertising: The interactive role of products and self-monitoring. Journal of Consumer Psychology, 1(4), 337–364. https://doi.org/10.1016/S1057-7408(08)80059-9
Sherif, M., & Hovland, C. I. (1961). Social judgment: Assimilation and contrast effects in communication and attitude change. Oxford, England: Yale Unversity Press.
Silvia, P. J., & Kashdan, T. B. (2009). Interesting Things and Curious People: Exploration and Engagement as Transient States and Enduring Strengths. Social and Personality Psychology Compass, 3(5), 785–797. https://doi.org/10.1111/j.1751-9004.2009.00210.x
Snyder, C. R., & Lopez, S. J. (Eds.). (2002). Handbook of positive psychology. Oxford [England] ; New York: Oxford University Press.
Sobkowicz, P. (2018). Opinion Dynamics Model Based on Cognitive Biases of Complex Agents. Journal of Artificial Societies and Social Simulation, 21(4), 24. https://doi.org/0.18564/jasss.3867
Soldz, S., & Vaillant, G. E. (1999). The Big Five Personality Traits and the Life Course: A 45-Year Longitudinal Study. Journal of Research in Personality, 33(2), 208–232. https://doi.org/10.1006/jrpe.1999.2243
Soroka, S., & McAdams, S. (2015). News, Politics, and Negativity. Political Communication, 32(1), 1–22. https://doi.org/10.1080/10584609.2014.881942
Spencer-Oatey, H. (2012). What is culture? A compilation of quotations. Retrieved from https://warwick.ac.uk/fac/soc/al/globalpad/openhouse/interculturalskills_old/global_pad_-_what_is_culture.pdf
Statista. (2016). Netherlands: Electricity DSO market share 2016. Retrieved June 4, 2019, from Statista website: https://www.statista.com/statistics/878534/electricity-dso-market-share-in-the-netherlands/
Stern, P. C. (2000). Toward a Coherent Theory of Environmentally Significant Behavior. Journal of Social Issues, 56(3), 407–424.
Stets, J. E., & Burke, P. J. (2000). Identity Theory and Social Identity Theory. Social Psychology Quarterly, 63(3), 224. https://doi.org/10.2307/2695870
Stolle, D., Soroka, S., & Johnston, R. (2008). When Does Diversity Erode Trust? Neighborhood Diversity, Interpersonal Trust and the Mediating Effect of Social Interactions. Political Studies, 56(1), 57–75. https://doi.org/10.1111/j.1467-9248.2007.00717.x

Stroud, N. J. (2010). Polarization and Partisan Selective Exposure. Journal of Communication, 60(3), 556–576. https://doi.org/10.1111/j.1460-2466.2010.01497.x

Sunstein, C. R. (1996). Social Norms and Social Roles. Columbia Law Review, 96(4), 903–968. https://doi.org/10.2307/1123430

Sustainable Development Commission. (2006). I will if you will: Towards sustainable consumption. Retrieved from Dept. for International Development website: https://research-repository.st-andrews.ac.uk/handle/10023/2312

Swierstra, T. (2013). Nanotechnology and Technomoral Change. Ethics and Politics, 15(1), 200–219.

Swierstra, T. (2015). Identifying the normative challenges posed by technology's 'soft' impacts. Etikk i Praksis - Nordic Journal of Applied Ethics, 9(1). https://doi.org/10.5324/eip.v9i1.1838

Swierstra, T., Stemerding, D., & Boenink, M. (2009). Exploring Techno-Moral Change: The Case of the ObesityPill. In P. Sollie & M. Düwell (Eds.), Evaluating New Technologies (Vol. 3, pp. 119–138). https://doi.org/10.1007/978-90-481-2229-5_9

ten Broeke, G., van Voorn, G., & Ligtenberg, A. (2016). Which Sensitivity Analysis Method Should I Use for My Agent-Based Model? Journal of Artificial Societies and Social Simulation, 19(1), 5.

Tesser, A, & Shaffer, D. R. (1990). Attitudes and Attitude Change. Annual Review of Psychology, 41(1), 479–523. https://doi.org/10.1146/annurev.ps.41.020190.002403

Thiriot, S., & Kant, J.-D. (2008). Using associative networks to represent adopters' beliefs in a multi-agent model of innovation diffusion. Advances in Complex Systems, 11(2), 261–272. https://doi.org/10.1142/S0219525908001611

Thorngate, W., & Tavakoli, M. (2009). Simulation, Rhetoric, and Policy Making. Simulation & Gaming, 40(4), 513–527. https://doi.org/10.1177/1046878108330539

Trafimow, D., & Sheeran, P. (1998). Some Tests of the Distinction between Cognitive and Affective Beliefs. Journal of Experimental Social Psychology, 34(4), 378–397. https://doi.org/10.1006/jesp.1998.1356

Tsfati, Y., & Peri, Y. (2006). Mainstream Media Skepticism and Exposure to Sectorial and Extranational News Media: The Case of Israel. Mass Communication and Society, 9(2), 165–187. https://doi.org/10.1207/s15327825mcs0902_3

Tversky, A., & Kahneman, D. (1974). Judgment under Uncertainty: Heuristics and Biases. Science, 185(4157), 1124–1131.

Unruh, G. C. (2000). Understanding carbon lock-in. Energy Policy, 28(12), 817–830. https://doi.org/10.1016/S0301-4215(00)00070-7

Urbig, D., & Malitz, R. (2005). Dynamics of structured attitudes and opinions. Representing Social Reality. Pre-Proceedings of the Third Conference of the European Social Simulation Association (ESSA), 206–212.

van Dam, K. H. van, Nikolic, I., & Lukszo, Z. (Eds.). (2013). Agent-based modelling of socio-technical systems. Dordrecht ; New York: Springer.

van de Poel, I. (2016). An Ethical Framework for Evaluating Experimental Technology. Science and Engineering Ethics, 22(3), 667–686. https://doi.org/10.1007/s11948-015-9724-3

van de Poel, I. (2018). Design for value change. Ethics and Information Technology. https://doi.org/10.1007/s10676-018-9461-9

van de Poel, I., & Royakkers, L. (2011). Ethics, Technology, and Engineering. West Sussex, United Kingdom: John Wiley & Sons, Ltd., Publication.

van Vuuren, D. P., Boot, P. A., Ros, J., & Hof, A. F. (2017). The Implications Of The Paris Climate Agreement For The Dutch Climate Policy Objectives. 29.

Verbong, G., & Geels, F. (2007). The ongoing energy transition: Lessons from a socio-technical, multi-level analysis of the Dutch electricity system (1960–2004). Energy Policy, 35(2), 1025–1037. https://doi.org/10.1016/j.enpol.2006.02.010

Vermeulen, B., & Pyka, A. (2016). Agent-based Modeling for Decision Making in Economics under Uncertainty. Economics: The Open-Access, Open-Assessment E-Journal. https://doi.org/10.5018/economics-ejournal.ja.2016-6

Verplanken, B., & Holland, R. W. (2002). Motivated Decision Making: Effects of Activation and Self-Centrality of Values on Choices and Behavior. Journal of Personality and Social Psychology, 82(3), 15.

Voicu, B., & Telegdy, B. (2016). Dynamics of Social Values: 1990–2012. Social Analysis, 6(1), 7–30.

Vringer, K., Aalbers, T., & Blok, K. (2007). Household energy requirement and value patterns. Energy Policy, 35(1), 553–566. https://doi.org/10.1016/j.enpol.2005.12.025

Waelbers, K., & Swierstra, T. (2014). The Family of the Future: How Technologies Can Lead to Moral Change. In J. van den Hoven, N. Doorn, T. Swierstra, B.-J. Koops, & H. Romijn (Eds.), Responsible Innovation 1 (pp. 219–236). https://doi.org/10.1007/978-94-017-8956-1_12

Weaver, D. H. (2007). Thoughts on Agenda Setting, Framing, and Priming. Journal of Communication, 57(1), 142–147.

Welzel, C., Inglehart, R., & Kligemann, H.-D. (2003). The theory of human development: A cross-cultural analysis. European Journal of Political Research, 42(3), 341–379. https://doi.org/10.1111/1475-6765.00086

Wilson, C., & Dowlatabadi, H. (2007). Models of Decision Making and Residential Energy Use. Annual Review of Environment and Resources, 32(1), 169–203. https://doi.org/10.1146/annurev.energy.32.053006.141137

Wilson, D. S., Van Vugt, M., & O'Gorman, R. (2008). Multilevel Selection Theory and Major Evolutionary Transitions: Implications for Psychological Science. Current Directions in Psychological Science, 17(1), 6–9.

Wittman, T. (2008). Agent-Based Models of Energy Investment Decisions. Springer Science & Business Media.

Wolf, I., Schröder, T., Neumann, J., & de Haan, G. (2015). Changing minds about electric cars: An empirically grounded agent-based modeling approach. Technological Forecasting and Social Change, 94, 269–285. https://doi.org/10.1016/j.techfore.2014.10.010

Wolske, K. S., Stern, P. C., & Dietz, T. (2017). Explaining interest in adopting residential solar photovoltaic systems in the United States: Toward an integration of behavioral theories. Energy Research & Social Science, 25, 134–151. https://doi.org/10.1016/j.erss.2016.12.023

Zajonc, R. B. (1980). Feeling and Thinking: Preferences Need No Inferences. American Psychologist, 35(2), 151–175.

Zillig, L. M. P., Hemenover, S. H., & Dienstbier, R. A. (2002). What Do We Assess when We Assess a Big 5 Trait? A Content Analysis of the Affective, Behavioral, and Cognitive Processes Represented in Big 5 Personality Inventories. Personality and Social Psychology Bulletin, 28(6), 847–858. https://doi.org/10.1177/0146167202289013