Exploring and Closing the Attitude-Behaviour Gap in Residential Energy Consumption.

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Executive Summary

The global transition towards sustainable energy usage requires everyone to contribute. The yearly reports on climate change by The Intergovernmental Panel on Climate Change (IPCC) offer a disturbing reminder that despite the growing commitment from governments and private companies, a rise in global temperature is inevitable. To reach the long-term goals for both 2030 and 2050 stipulated in the Paris climate agreement, both consumers and producers play a crucial role.

Limiting climate change is imperative, but when consumers are tasked with making behavioral changes convenience and cost remain predominant barriers. Even if it is in the best interest of the consumer to invest in energy-efficient technologies, investment does not occur, and technologies remain underutilized. In other words, there remains a complex issue where the adoption rate of energy-efficient technologies does not reach its full potential. An asymmetry is observed between consumer attitudes towards sustainability and their actual choices regarding energy consumption. This is an issue for climate change mitigation measures, specifically demand side solutions, due to the asymmetry causing an overestimation of their effectiveness.

This asymmetry is often referred to as the attitude-behaviour gap. Consumers are not rational in their choices, but are rather 'boundedly-rational', in particular regarding environmental issues. Cognitive limitations constrain our decision-making, especially when consequences of our actions are distanced in space and time, as is true for global warming.

What exactly causes the emergence of the attitude-behaviour gap, and to what extent, is not fully understood. Previous academic research has shown that many barriers to adoption remain, and that difficulty lies in the heterogeneity of consumers. Potential explanations are generally market failures or behavioural effects. Indeed, a list of potential behavioural and psychological factors is presented in various publications, but it is unknown to what extent they contribute towards the emergence of the attitude-behaviour gap. Nevertheless, roughly 30% of potential savings energy from energy-efficient technologies are left on the table. Therefore, closing the gap by increasing the rate of adoption of energy-efficient technologies has great potential and is relevant to producers and policymakers to further reduce energy consumption and greenhouse gas emissions.

Through the use of a simulation model this thesis explores the emergence of the attitude-behaviour gap by analyzing the decision-making behaviour of heterogenous Dutch households, parametrized by real-world survey data. Ultimately, to close the gap by lowering the barriers to adoption with policy interventions. An agent-based simulation model (ABM) has been developed to address the main research question:

To which extent can different psychological factors influence the emergence of the attitude-behaviour gap in household energy consumption, and what policy interventions can be employed to close the gap?

A synthetic population of households is generated with a combinatorial optimization approach based on individual-level survey data. Every timestep, households choose whether to stick to the status quo or to invest in solar photovoltaics, depending on the dynamic environmental, economic, and social utility. Decision-making is implemented at a household level based on the Theory of Planned Behaviour (TPB), and households share information with other households through a social network.

A time-dependent global sensitivity analysis (GSA) was conducted to address the first part of the research question. Factors analyzed in this experiment are the perceived behavioural control of households, the importance of their initial beliefs, the influence of social learning, and the resistance towards solar PV investments due to economic uncertainty.

Model results indicate economic factors contribute towards the emergence of the attitude-behaviour gap to a greater extent than social factors, especially in later stages of the simulation, when the diffusion process has slowed down and has almost reached saturation. The main economic barriers to adoption are (1) the financial benefits compared to the high upfront cost, and (2) the economic uncertainty regarding the future due to a lack of information. In the model consumers demonstrate irrationally risk-averse behaviour, despite the high probability gains from electricity cost savings and uncertain low probability losses from changes in the electricity price or policy interventions in the future.

Nevertheless, the importance of the social factors should not be overlooked because model results indicate that social effects have a strong impact on the emergence of the attitude-behaviour gap and diffusion rates in general. Households consider the perception about the attitude of others and social expectation, this leads to social pressure and social comparisons between households, especially with trusted social connections. Results indicate that early adopters in the model generally install solar PV due to personal reasons; economic or environmental. While later adopters tend to be more socially oriented and are encouraged by social effects, when a large part of the population has already adopted solar PV and the social pressure to adopt is higher.

A second GSA has demonstrated that the operationalization of the perceived behavioural control (PBC) component of TPB has a significant impact on the model results. This illustrates that the perception of affordability that is represented by the PBC component has a significant impact on the emergence of the attitude-behaviour gap, but is heavily dependent on the operationalization of the TPB.

The second part of the research question is addressed with exploration of the Dutch *salderingsregeling* (feed-in tariff) and *BTW-aftrek* (tax rebates). In the model, both are effective in making solar PV more appealing for small-scale users, increasing adoption rates significantly by lowering the economic barriers for households. Even for households that hold positive attitudes towards the environment, the economics remain an important aspect that ultimately determines their behaviour, and by structuring policies that specifically address these economic barriers the attitude-behaviour gap can be shrunk.

Considering the current energy crisis in Europe due to the invasion of Ukraine, simulation experiments with high energy price scenarios have been conducted as well. In these scenarios a range of prices from the historic price of 2021 to the current price of approximately 0.77 €/kWh is considered. These experiments are added to evaluate the robustness of policy interventions in extreme situations. In scenarios with electricity prices above 0.2 €/kWh the economic benefits for households that adopt solar PV are so significant that very high adoption rates are observed, and the impact of policy interventions and how they are implemented are close to negligible.

These conclusions must be considered with the following limitations in mind. Firstly, the survey was conducted once, without follow-up to check whether the respondents actually adopted solar PV installations as they intended, rendering traditional validation difficult. It also implies that the survey data did not measure behaviour, but rather expected action. This presents an opportunity for future research to parametrize the model with different survey data.

Secondly, the survey data did not include information on the social network, therefore the social network was represented by a small-world network, established with parameters based on similar literature. Ideally the social network characteristics are established on empirical data to reduce the number of assumptions and increase the strength of the conclusions on social factors.

Thirdly, due to technology specificity the results may not generalize to other energy-efficient technologies and may only be relevant for solar PV, as factors that households consider when choosing to adopt a certain energy-efficient technology is strongly technology dependent.

Lastly, the exploration of the policy interventions was limited to only two financial instruments. This does not imply that these two policy interventions, or financial policy interventions in general, are the only effective interventions for closing the attitude-behaviour gap. Information-based policy instruments and regulatory instruments could not be explored due to time constraints but may a play important role in closing the gap. Future research could simulate the impact of regulatory approaches or informative & voluntary schemes, or combinations of policy interventions. Along with policy interventions focused on more complicated solutions, such as tradeable certificates or tenders.

In short, the abovementioned limitations were generally introduced due to modelling choices that had to be made due to time constraints and lack of data. Indeed, data availability was the main limitation of this research, the survey offered a strong empirical foundation, but it also limited the research somewhat because the survey had already been conducted and the survey was not longitudinal. With more suitable survey data the model could be used in future studies to explore the gap and other policy interventions.

In this study, the exploration of the emergence of the attitude-behaviour gap, and the contribution of various psychological factors, was successfully explored and has generated insights that may hopefully guide policymakers towards closing the gap to promote the energy transition.

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1 Introduction

1.1. Research Problem

The global transition towards clean energy requires everyone to contribute. The global energy consumption is set to grow 30 to 50 percent in the next 25 years (Gerarden et al., 2015). The Intergovernmental Panel on Climate Change (IPCC) reports on climate change offer a shocking reminder that despite the growing commitment from governments and private companies a rise in global temperature is inevitable. We have already passed the point where even the most optimistic scenario brings a global temperature increase of 1.5C (IPCC Working Group II, 2022).

To reach the long-term goals for both 2030 and 2050 stipulated in the Paris climate agreement, the Ministry of Economic Affairs and Climate Policy has taken steps to reduce greenhouse gas (GHG) emissions in The Netherlands (PBL, 2020). Alongside the controversial phasing out of gas production in Groningen, the Ministry of Economic Affairs and Climate Policy has been coordinating, funding, and executing a wide range of alternatives (Ministerie van Economische Zaken en Klimaat, 2021). The share of solar and wind in the total energy consumption increased with 13.7% in 2019, indicating a growing trend towards replacing fossil fuels with renewable energy production (PBL, 2020). However, in 2019 only a mere 8.7% of the total national energy consumption was from renewable sources, and only a reduction in GHG of 18% has been achieved compared to 1990, demonstrating that the actions being taken are not sufficient (PBL, 2020).

With the current pace the 2030 Paris goal of 49% GHG reduction will not be reached in The Netherlands, highlighting the problem at hand (PBL, 2020). This problem is exacerbated by the current energy crisis caused by the invasion of Ukraine, which has significantly decreased gas supply and increased gas prices, resulting in polluting coal power plants such as the largest power plant in The Netherlands being forced to run at full capacity (Heijn, 2022; NOS, 2022a), until more renewable energy generation can be established.

In the Netherlands, electrification of industry, electrification of transportation, and the nationwide movement towards gas-free households is weighing heavily on the energy system. The rapid increase in the supply of renewables with their intermittent nature, and the increasing electricity demand in general has necessitated demand side management. Indeed, the responsibility does not rest solely on the shoulders of policymakers and energy producers. On the demand side the consumer plays an important role in the energy transition with their energy consumption behavior and sustainable consumption in general. Small scale consumers and households are responsible for 84 petajoule of the yearly electricity consumption and the emission of 23.3 megaton of CO_2 equivalent in 2019 (PBL, 2020). The residential sector was responsible for roughly 14% of the total energy consumption in the Netherlands in 2021 (CBS, 2022b). Opportunities arise for new businesses who offer innovative energy-efficient technologies promising benefits towards reducing household energy use. For instance, the average household consumption is projected to decrease from 3100 kWh to 2600 kWh due to an increase in household renewables such as solar photovoltaics (PV) for personal electricity generation (PBL, 2020). Additionally, the rise of 'prosumers' using solar photovoltaics is projected to produce 35% of the electricity consumed in households in 2030 (PBL, 2020). More often consumers are making environmentally conscious decisions, solar photovoltaics are just one of the examples underlining the general change in attitude towards sustainability (CBS, 2018, 2020a).

For consumers limiting climate change is imperative, but when tasked to make behavioral changes convenience and cost remain predominant (Henderson & Anupama, 2021; Rahmatallah Poudineh; Penyalver, 2020). More specifically to the energy context, there remains a complex issue where the adoption rate of energy-efficient technologies such as PV, batteries, efficient lighting, and smart meters do not reach their full potential (Jaffe & Stavins, 1994; Pelenur & Cruickshank, 2012). Even if it is in the best interest of the consumer to invest in energy-efficient technologies, investment does not occur, and technologies remain underutilized. This issue of private optimality is referred to as the "energy paradox". The broader concept relating to social optimality—whether technologies are socially efficient to adopt—is defined as the "energy-efficiency gap" (Gerarden et al., 2015). The gap is estimated to be roughly 30% of the full potential savings (Weber, 1997). The issue that arises regarding sustainable consumption is the asymmetry between the consumer attitude towards sustainability, and their actual choices when it comes to energy consumption behavior (Niamir et al., 2020). Demand side solutions are deemed promising climate change mitigation measures, but their effectiveness may be overestimated due to the gap between what could potentially be achieved and the way people actually behave (Creutzig et al., 2018).

Governments worldwide have taken steps to address the issue in multiple ways, by supporting R&D programmes, grants, and public procurement to support innovative energy-efficient technologies (Henderson & Anupama, 2021). More consumer-focused interventions such as dynamic pricing to shift demand and feed-in tariffs are also considered by governments. The difficulty remains the participation of consumers and their heterogeneity; policy interventions that stimulate some may have no effect on others. Many types of barriers to adoption (structural, economic, social, and behavioural) still remain (Hesselink & Chappin, 2019).

1.2. Research Objective

The objective of this research is to explore the attitude-behavior gap, simulating the decision-making behavior of heterogenous consumers in a household energy consumption context. Petajoules of potential energy savings are left on the table every year due to a psychological phenomenon, imploring further investigation into the cause and into feasible interventions. Simulation models are ideal for simulating complex adaptive systems and analyzing the emergent behaviour such as technology adoption rates. A simulation model can capture technological aspects such as the energy-efficient technology diffusion and technical characteristics of specific technologies, in addition to social aspects such as household heterogeneity, social norms and social networks through which information propagate between different households. By studying and implementing the household behaviour at a low level, the resulting system level changes and emergent behaviour can be analyzed. Subsequently interventions that can address barriers to adoption and aid in closing the attitude-behaviour gap can be tested in the model.

The modelling approach will be used to simulate heterogenous households parameterized by real-world survey data. Decision-making is implemented at a household level based on the Theory of Planned Behaviour (TPB) (Ajzen, 1991). Households interact with one another by sharing information regarding energy-efficient technologies in a small-world social network connecting households, weighed by their age, education, and income parity. Every step, households choose whether to invest in energy-efficient technologies depending on the dynamic environmental, economic, and social utility.

1.3. Research Scope

The focus of the research lies on the demand-side behaviour of energy consumers in the Netherlands, specifically households that are represented by agents. Households are heterogenous and empirically grounded with single-user survey data of Dutch households. Households share information through social networks based on distance and income level. Households can choose to invest in energy-efficient technologies, they make choices based on factors such as their environmental awareness and self-efficacy. Energy distribution and the electrical grid are demarcated and therefore not represented in the model. The supply side is exogenously modelled with data from the Central Bureau of Statistics (CBS). Solar PV is the energy-efficient technology represented in the model due to survey data availability. The effects of introducing various policy interventions are explored, in addition to the phasing-out of existing Dutch policy such as the *salderingsregeling*.

This topic is relevant for the CoSEM programme because the attitude-behaviour gap is a complex problem that emerges in the energy system. A mix of heterogenous stakeholders is involved in operating and maintaining this sociotechnical system, consumers on the demand side and energy suppliers on the supply side, and more recently ‘prosumers’ such as households with solar PV. On the physical layer there exists a complex energy network with infrastructure such as high voltage transmission lines, transformers, distribution networks, decentralized energy generation such as solar PV, centralized generation units, and energy-consuming technologies. On the institutional layer, governments bear responsibility to stimulate the adoption of residential energy saving technologies to overcome economic, social, and behavioural barriers present in consumer behaviour, one example being the Dutch *salderingsregeling* for stimulating decentralized solar generation for small-scale users.

1.4. Thesis Structure

The following chapter presents the literature review that has been conducted to get a better understanding of the historical backdrop and state-of-the-art developments in energy ABM, concluding with the knowledge gap. Chapter 3 covers the research objectives, main research question, and sub questions. In chapter 4 the research methods and high-level model design used to address the research questions is presented, in addition to the experimental design. Chapter 5 shows the conceptualization process of the model components, the TPB operationalization, and survey data analysis. Chapter 6 follows with the model formalization and software implementation, including the parametrization, KPIs, and model verification. The results are presented in chapter 7 and the results are analyzed and discussed in chapter 8, in addition to the model validation. In chapter 9 the research questions are explicitly addressed. The final chapter, chapter 10, the scientific and societal contribution are discussed, and future research directions are suggested based on the limitations.

2 Literature Review

The goal of this chapter is to introduce core concepts that are key in understanding this research by method of literature review. The historical backdrop of previous works is sketched, and a literature sample is explored. Based on the current literature a knowledge gap is identified.

2.1. Review Methodology

The method of conducting a literature review given by (Banister & Van Wee, 2015) is applied. The authors recommend being explicit in the methodologies used and in the selection process. Therefore, this first section will shortly discuss the search strategy, article retrieval process and selection procedure. The search is conducted in Elsevier's Scopus. Only scientific journal articles written in English are considered. The search is limited to titles, abstracts, and keywords. Within these sections the following three key terms are searched: Energy or electricity, variations of ABM, and household or consumer or residential, with the intention of capturing ABMs of consumer energy-efficient technology adoption or usage. This is achieved with the string: TITLE-ABS-KEY (("energy" OR "electricity") AND ("agent-based model*" OR …) AND ("household*" OR "consumer*" OR "residential")). The initial search query identified 214 articles. The selection criteria for downscoping were the year of publication and the number of citations. Articles with only storage technologies, or co-sim/multiformalism/multi-level approaches are not considered in this review. Because the focus is on ABM, only simulation models are considered as per the categorization of (Mundaca et al., 2010), other types of models such as accounting or optimization models are demarcated. The snowball method was utilized to find more relevant sources, resulting in two extra publications being added to the final sample. Ultimately, 11 articles were selected based on the selection criteria described above. The selection process is illustrated in figure 1 shown below. In Appendix A the resulting literature sample can be found in table format.

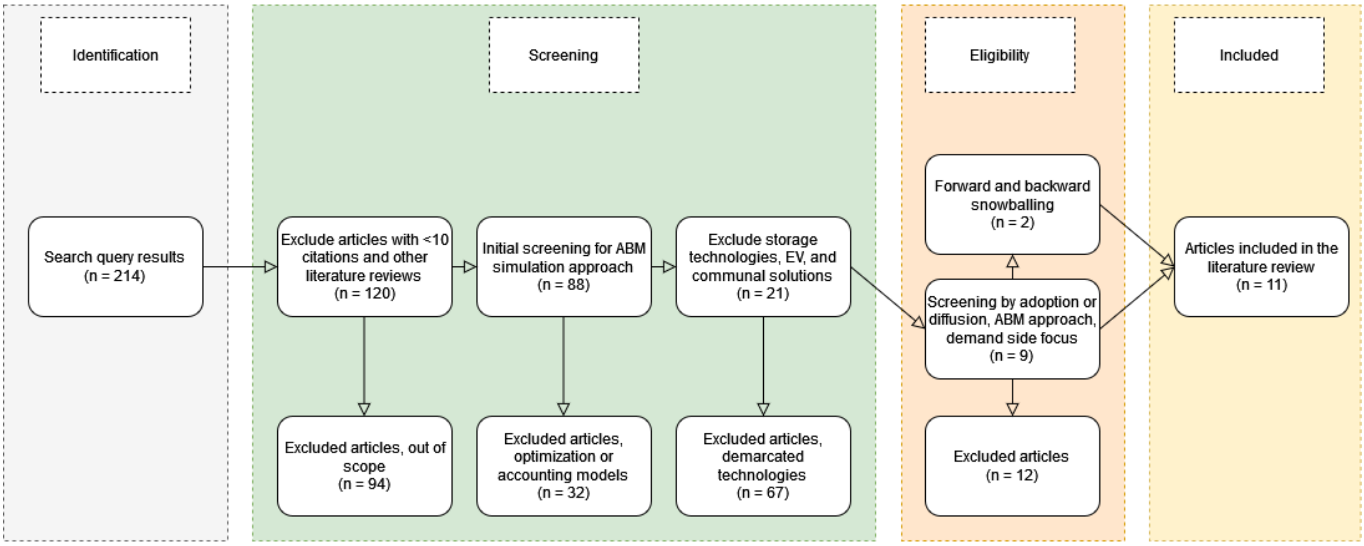


Figure 1
Flowchart presenting the literature review selection process.

2.2. Review of state-of-the-art

Before examining the literature review sample, some background knowledge of the historical backdrop, underlying mechanics, and core concepts relevant to the research area is required. This section offers deeper insight into the relevant concepts.

2.2.1. Energy-efficient Technologies

Energy-efficient technologies is a broad term meaning technology that can achieve the same services and performance of legacy technology while using less energy (European Comission, 2011). The focus of the literature review is on the residential sector, this constraint results in a smaller subsample of energy-efficient technologies that households are able to install and use. In the final literature sample a wide range of energy-efficient technologies are represented, from most to least represented: solar photovoltaics (PV), electric vehicles (EV), batteries, efficient lighting, ventilation, heating systems, and dynamic tariffs. Generally, the authors choose one specific technology to model, with the exception of the combination solar PV and battery technology studied by Alyousef et al. (2016) and Bellekom et al. (2016). This so-called *technology specificity* is a key aspect of designing ABMs, because the factors that households consider when choosing to adopt a certain energy-efficient technology is strongly technology dependent (Moglia et al., 2017). The way people make decisions about efficient lighting and solar PV is dependent on the product on offer, and the attributes of the products (Moglia et al., 2017). One could imagine that consumers may prefer certain light qualities such as color or level of illumination for aesthetics, while this is not relevant for solar PV at all.

However, this does not mean there are no generic factors affecting consumer decision-making that are shared by all energy-efficient technologies. Generic factors are identified by Moglia et al. (2017) to include social norms, monetary factors, environmental benefits, and lifestyle considerations.

2.2.2. Attitude-behaviour Gap

The attitude-behaviour gap[1] is, put very plainly, the "difference what people say and what people do" (Blake, 1999). Psychology and behavioural economics show there exists an asymmetry between consumers' attitude and their decision-making behavior. The existence of such a gap was demonstrated as far back as 1957 by Festinger in his book on cognitive dissonance. In other words, possessing pro-environmental values is not the same as engaging in pro-environmental behaviour (Jackson, 2005; Newton & Meyer, 2013). This ties in with the idea that humans are not rational in their choices, as Simon (1957) stated in his Nobel-winning critique on the rational choice model. He used the term bounded rationality, and Jackson (2015) further argues that environmental issues in particular support bounded rationality. Consumers are constrained by cognitive limitations; they are not fully aware of the consequences of their actions and are uncertain because consequences are distanced from them in space or time (Jackson, 2005). Take for instance the long-term effects of global warming or GHG emissions.

[1] Synonymous with the value-action gap, knowledge-action gap, knowledge-practice gap, intention-behaviour gap, or belief-behaviour gap

Furthermore, there is a more refined concept when the attitude-behaviour gap occurs in an energy context. The ‘energy efficiency gap’ is the term used for a complex issue where the adoption rate of energy-efficient technologies does not reach their full potential that would be economically-efficient (Jaffe & Stavins, 1994; Pelenur & Cruickshank, 2012). Here, technologies refer to innovations for reducing energy costs and environmental damages such as household PV, heat pumps, lighting technologies, electric vehicles, and smart meters. In the case of energy-efficient technologies, ‘not reaching their full potential’ means that households do not engage in behaviour that would be justified, even if there are personal financial net benefits. This issue of private optimality is referred to as the ‘energy paradox’. The broader concept relating to social optimality, whether technologies are socially efficient to adopt, is defined as the ‘energy-efficiency gap’ (Gerarden et al., 2015). Adoption of energy-efficient technologies can not only realize private benefits, but also environmental, economic, and social benefits. There are barriers to adoption that lead to the suboptimal diffusion of cost-effective energy-efficient technologies (Shama, 1983).

This phenomenon occurs so frequently, that the energy efficiency gap is estimated to be roughly 30% of the full potential savings (Weber, 1997). Therefore, increasing the rate of adoption for energy-efficient technologies has great potential and is relevant to producers and policymakers to further reduce energy consumption and GHG emissions. Unfortunately, there are still many uncertainties surrounding the topic (Hesselink & Chappin, 2019). Under what conditions do consumers adopt these technologies? What are the barriers to adoption? What human biases play a role? What interventions are most effective in closing the gap? Are the interventions generalizable to multiple countries?

The potential explanations for the energy efficiency gap generally fall into three broad categories: (1) market failures, (2) behavioral effects, and (3) modeling flaws (Gerarden et al., 2015). The focus of this research is the second category, behavioral affects. Examples of potential barriers to adoption include salience issues, inertia, short-sightedness, heuristic decision-making, prospect theory, and systematically biased beliefs (Gerarden et al., 2015).

The analysis by Jaffe & Stavins (1994) provides a framework for potential explanations and further discerns between energy-efficiency gaps. Most research is focused on the ‘true social optimum’ (see figure 2), because this is most relevant to policymakers who seem to give more weight to environmental considerations in energy policy objectives (Jaffe & Stavins, 1994).

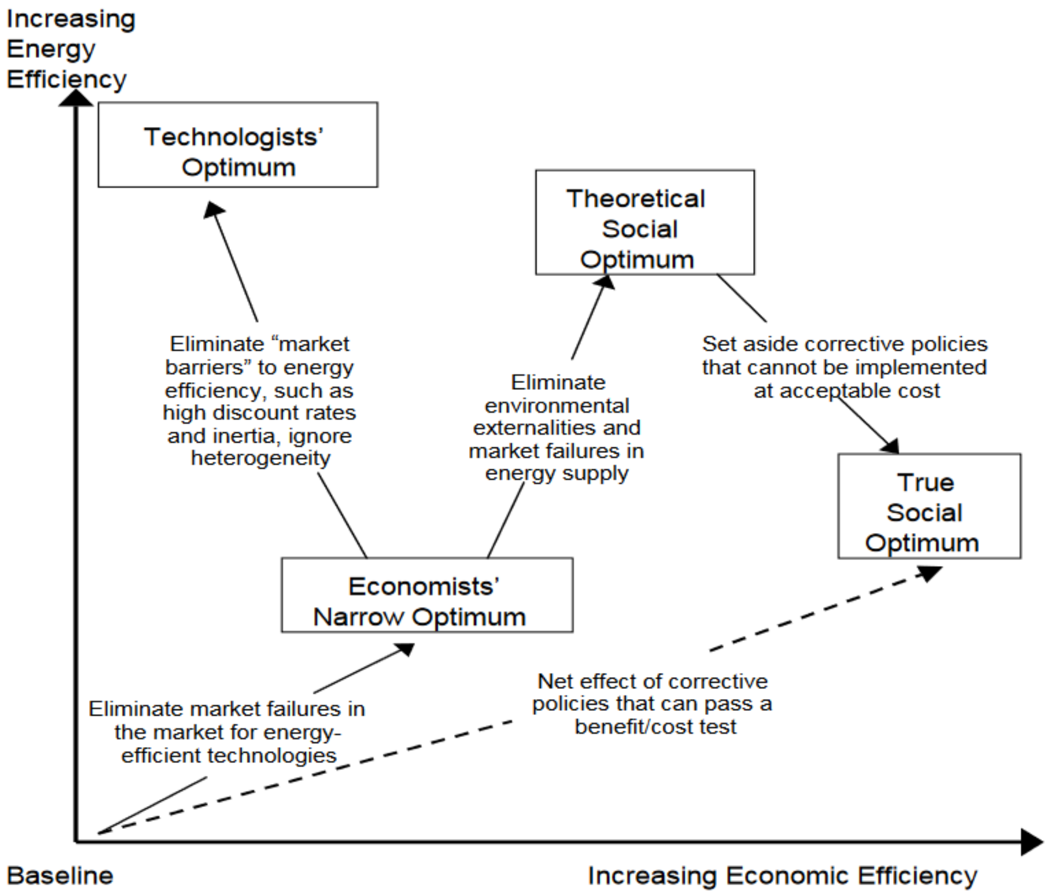


Figure 2
Alternative notions of the energy-efficiency gap by Gerarden, Newell & Stavins, 2015. Adapted from Jaffe & Stavins (1994). The authors note that the distances are a matter of opinion.

2.2.3. Decision-making Theories

The way ABMs implement human decision-making is often based on a theoretical foundation. This helps structure the decision-making process by basing it on psychological research that is supported by empirical evidence. This is strongly advised for diffusion simulation models because it provides a rigorous theoretical framework (Moglia et al., 2017). The theoretical framework that underpins behavioural components provides a strong starting point for understanding and addressing environmental problems (Steg & Vlek, 2009).

Classical economic theories state that human decision-making is based on rational choice. Rational choice theory suggests people aim to maximize utility, act on relevant information, and have rational preferences amongst outcomes (Goode, 1997). Meaning they would make optimal decisions given certain constraints. However, in stark contrast with classical economic theories, in reality people are rarely rational decision-makers. Systematic human biases and other underlying psychological phenomena create a mismatch between the rational choice and the choice people tend to make. People are viewed as *boundedly rational*, demonstrating satisficing behaviour instead of utility maximization (Kahneman, 2003; Simon, 1957). People make mental shortcuts to process the massive amounts of information and choices they encounter daily, because they possess only limited cognitive resources (Kahneman et al., 1982). Because people are showing boundedly rational behaviour, simply giving them more options (different energy-efficient technologies) or more information by increasing knowledge or awareness, will not result in the desired energy savings.

The theory of planned behaviour (TPB) is the successor of the theory of reasoned action proposed by Ajzen & Fishbein (1975). It is widely used in a variety of areas where behaviour and more specifically human decision-making plays a role. It is also the most represented theory in the literature sample to study technology diffusion with ABMs (Claudy et al., 2013; Jensen et al., 2016; Maya Sopha et al., 2011; Rai & Robinson, 2015) and commonly used in energy ABMs (Hesselink & Chappin, 2019). The theory suggests that a person's intention to engage in certain behaviour is determined by three factors: (1) personal attitudes, (2) subjective norms, and (3) perceived behavioural control (PBC). Personal attitudes consist of our knowledge, attitudes, and biases. Subjective norms consider our perception about the attitude of others, the perceived social pressure to perform an action or not. PBC is our belief of how much we can control our behaviour, similar to self-efficacy or locus of control. This can be both internal (determination, own ability) or external (resources, available support). If we believe to have a higher level of control over a situation, we are more likely to exert more effort to succeed. In short, the behaviour of a person is determined by the intention and their perceived behavioural control over the situation.

In the literature sample a wide range of theories is used as theoretical foundation to structure the decision-making processes. Affect control theory is used to analyze and predict solar PV and battery adoption in Germany (Alyousef et al., 2017). Noori & Tatari (2016) use a utility function to model consumer decision-making when purchasing electric vehicles. Other theories represented are behavioural reasoning theory (Claudy et al., 2013), and value-belief-norms (Kowalska-Pyzalska et al., 2014). One publication in the final sample does not use a theory for decision-making and agents are instead fully rational (Bellekom et al., 2016). The most represented is Ajzen's *theory of planned behaviour* to study both diffusion (Claudy et al., 2013; Jensen et al., 2016; Maya Sopha et al., 2011; Rai & Robinson, 2015) and usage of energy-efficient technologies amongst households (Kowalska-Pyzalska et al., 2014). Perhaps the wide variety of theories used underlines the uncertainty regarding the most suitable theory for modeling household energy consumption behaviour. This is not unsurprising as there is no universally accepted and objective choice of theory stemming from social sciences, referred to as the 'incoherency problem' (Chappin et al., 2019; Schlüter et al., 2017). Besides the choice of theory, Dressler & Schulze (2016) also raise concerns about the irregular way modellers interpret qualitative social science theories in quantitative ABMs. It is often up to the modellers discretion how qualitative social theories are operationalized in the model, leading to enormous flexibility. This methodological challenge is also studied by Muelder & Filatova (2018) in their publication on different implementations of TPB. Another important consideration is under what conditions the chosen theory remains successful (Steg & Vlek, 2009), it is important that results are generalizable so they are relevant in more situations.

A variety of findings is seen in the literature. Kowalska-Pyzalska et al. (2014) indicates that the size of the attitude-behaviour gap depends on decision time of the households, when decision time is long the gap is larger, the size of the attitude-behaviour gap is not moderated by attitude accessibility but by the attitude's temporal stability, how much it can fluctuate in time (Kowalska-Pyzalska et al., 2014). Research by Claudy et al. (2013) concluded that the attitude-behaviour gap can be closed if consumers can act on positive attitudes by reducing barriers to adoption. In contrast to Maya Sopha et al. (2011), who suggests norm-related interventions are less important than the technology-specific attributes such as reliability. The effectiveness of interventions may also be dependent on the amount of adopters due to social effects (Rai & Robinson, 2015), with rebates showing a larger effect when more households have adopted the technology. Additionally, information is more effective in changing environmental attitudes when the information is accessible and easy to understand, such as energy labels (Eppstein et al., 2011).

2.2.4. Barriers to Adoption & Policy Interventions

These two concepts are related in a sense that to spread energy-efficient technologies throughout the consumer market, the policy interventions must target the consumers' reason against adoption and reduce the barriers to adoption. Indeed, the particular barriers are often the reason why policies are created (Hesselink & Chappin, 2019). Policymakers may choose to employ available policy instruments in their arsenal to attain certain policy objectives, to ultimately reduce residential energy usage. This is achieved in two ways: they may (1) influence the behaviour of consumers or may (2) aim to reduce the barriers to adoption.

Focusing on consumer behaviour has two important advantages, it is a cost-efficient option to decrease CO2-emissions, and behaviour interventions are less likely to trigger 'rebound effects' (Jensen et al., 2016) where improvements in efficiency lead to cost reductions allowing consumers to buy and use more of the product in return. Additionally, the changed behaviour can influence the social norms of other households in the social network (Jensen et al., 2016).

Reducing barriers to adoption is a common strategy for policy interventions. In the literature sample the most common policy interventions are financial instruments, specifically subsidies. These aim to improve the cost-effectiveness of energy-efficient technologies.

A categorization made by Mundaca et al. (2010) splits energy efficiency policy interventions into three groups: (1) economic, financial and market-based instruments, (2) regulatory approaches, and (3) informative and voluntary schemes. The OECD (2014) recommends category three for educating the public about the environment and recommends category 1 instruments to support low-income households. Likely because the consumers who adopt solar PV are much wealthier than average (Rai & McAndrews, 2012). However, financial instruments may even be counterproductive in achieving the ideal behaviour, highlighting the boundedly rational human behaviour not in line with the rational choice model (Frederiks et al., 2015).

2.2.5. Diffusion of Innovative Energy Technologies

In the book Diffusion of Innovations, Rogers (2010) laid out the foundation of 'diffusion of innovation' models. An innovation refers to a new technology, adopted over time by members of society. In the book Rogers (2010) models human decision-making as five stages: knowledge, persuasion, decision, implementation, and confirmation. In general, these models were originally largely conceptual learning tools (Axelrod, 1997) but empirically grounded ABMs have experienced significant growth since then (Kiesling et al., 2012; Zhang & Vorobeychik, 2017). The first distinction that can be made is whether the publications are diffusion (adoption) models or usage models. In the sample the large majority of publications are diffusion of innovation models, only Bellekom et al. (2016) is a usage model. What sets the diffusion models apart is the underlying behavioural theory applied which is discussed in the next paragraph. In terms of historical backdrop, the sample supports the fact that the field is relatively young and likely underdeveloped; the earliest publications are from 2011 (Eppstein et al., 2011; Maya Sopha et al., 2011).

2.2.6. Social Dynamics

Social network theory originates from mathematical graph theory and has been used in social sciences and psychology to study social organization (Krause et al., 2007). While technology features are important for adoption and diffusion, the social aspects should not be neglected. Social networks play a crucial role in how information and perceptions are transferred between households, and consequently in how a technology diffuses in a population. However, a common issue is the lack of empirical data on how people spread information with each other (Delre et al., 2010). There is no single optimal structure for simulating social networks, but a more realistic option is 'small-world networks' characterized by short path lengths and high clustering, often displayed in communities (Delre et al., 2010; Watts & Strogatz, 1998). Indeed, people are prone to the influence of others in their social network, an evaluation by Allcott (2011) demonstrates that people who receive a letter if they use more energy than their neighbour will reduce their own energy consumption accordingly, underlining the influence of social norms on energy consumption behaviour. In diffusion ABMs the social network can be modified to include spatial proximity and similarity in social status or other sociodemographic characteristics (Schwarz & Ernst, 2009).

Research shows that social aspects such as communication are related to diffusion of solar PV systems (Jager, 2006; Maya Sopha et al., 2011; Shum, 2010). In reality information and opinions spread between households, and modellers attempt to emulate social dynamics with social networks. Most commonly small-world networks are used to represent how information can flow between households, with nodes being the households and edges the communication channels. In small-world networks, households interact with their neighbors and with a random fraction of the population that represent family, friends, or relatives. Energy-efficient technologies such as solar PV and hybrid vehicles show significant spatial structure, neighbors within a certain radius are influenced most (Rai & Henry, 2016). In the literature sample there exists a difference in the extent to which social interactions are represented. Firstly, some research does not implement a social network at all (Bellekom et al., 2016; Noori & Tatari, 2016), others instead opt for opinions based on the Moore neighborhood on a lattice (Kowalska-Pyzalska et al., 2014). Secondly, from those that do implement social networks most are based on geography (spatial distance) alone (Alyousef et al., 2017; Maya Sopha et al., 2011; Stavrakas et al., 2019) while others refine these further based on home-value similarity (Rai & Henry, 2016; Rai & Robinson, 2015) or lifestyle similarity (Jensen et al., 2016) or multiple characteristics such as age and salary (Eppstein et al., 2011) to further account for agent heterogeneity. Others do not explicitly state how the social dynamics are implemented (Afman et al., 2010). The importance of social dynamics also has implications for policy design, it may be efficient to target households with a higher social status to increase the effectiveness of policy interventions (Jensen et al., 2016).

2.2.7. Policy interventions

The policy interventions tested in the models from the literature sample are multifold. Firstly, financial policy instruments are most common in the sample, with Noori et al. (2016) testing federal and regional subsidies for electric vehicles in the US, recommendations on dynamic tariffs and information campaigns are offered by Kowalska-Pyzalska et al. (2014), and feed-in tariffs and their effect on adoption of PV-battery systems are analyzed by Alyousef et al. (2017). Net-metering (identical to the Dutch *salderingsregeling* for solar PV) is explored by Stavrakas et al. (2019) to analyze the impact on the adoption of solar PV. Rai & Robinson (2015) test financial rebates for low-income households. Effects of financial policy instruments such as taxes and subsidies, but also regulatory bans are tested to examine the impact on adoption rates (Afman et al., 2010). Secondly, policy instruments that stimulate the adoption of 'smart meters' or devices that provide instant feedback to the consumer regarding their consumption habits, Jensen et al. (2016) analyze the impact of smart meters that monitor and provide instant feedback to users of their CO_2 levels. Instead of focusing on a single intervention, Claudy et al. (2013) offers advice to policymakers on what instruments may provide additional reasons for adoption, reduce barriers to adoption, and reinforce environmental discourse. Similarly, research by Sopha et al. (2011) includes a wide variety of policy instruments ranging from regulation, financial aid, education, promotion, to technical development to improve reliability. Creating scenarios where multiple policy interventions are implemented simultaneously may offer insight into what interventions complement each other to reach policy objectives.

2.2.8. Energy ABMs

The strength of ABM lies in the bottom-up perspective and the agent heterogeneity; this makes it ideal to model complex adaptive systems and to explore possible emergent properties (Goldstone & Janssen, 2005; Nikolic & Ghorbani, 2011). Unlike traditional models that *describe*, "ABMs focus on the essence of the *process* that gives rise to the pattern." (Chappin et al., 2019), ideal for understanding how the attitude-behaviour gap is shaped. Traditional modelling paradigms implicitly assume that there is centralized control over the energy system, while this may not be the case for decentralized privately-owned technologies such as solar PV (Stavrakas et al., 2019). Additionally, ABM allows the possibility to introduce more elaborate decision-making logic for households (Hesselink & Chappin, 2019) to represent more realistic social dynamics, placing more emphasis on the behavioural component versus only the technical or economic components.

The ABM approach lends itself well to ex-ante policy intervention exploration to evaluate policy impacts. This exploratory approach is chosen to support conclusions based on a limited number of computational experiments (Bankes et al., 2013). By designing and testing interventions in an agent-based model, recommendations can be made for policymakers to take steps towards closing the attitude-behaviour gap to realize potential energy savings, and to ultimately accelerate the energy transition.

Nevertheless, Macal (2016) identifies several research challenges and limitations that must be addressed to realize the full potential of ABM. One of them being the behavioral modelling, the representation of human behaviour. In this research approach the weakness is addressed by constructing the agent behaviour based on established behavioural theory, specifically the Theory of Planned Behaviour (Ajzen, 1991). Additionally, the advantages of empirically grounded models relate to one of the weaknesses of ABMs; verification and validation (Macal, 2016). Traditional model validation is impossible for ABMs (Nikolic & Ghorbani, 2011), therefore other methods such as surveys are used. This also relates to the delicate balance in the complexity of the model. On the one hand, an oversimplified behavioural model would abstract human decision-making too much to be useful. On the other hand, an overambitious model may be hard to understand and difficult to validate, even with empirical data. Besides the ABM specific limitations, the limitations that restrict all modelling approaches still apply, i.e. the predictions provided are only provided under the conditions of the model (Boschetti et al., 2011).

2.3. Knowledge Gap

From the literature it became apparent that ABM is a promising modelling paradigm for studying the barriers to adoption and diffusion of energy-efficient technologies amongst households. However, some aspects remain inadequate or understudied. The main knowledge gap observed in the literature is the integration of social data, especially in energy efficiency research.

While it is true that ABMs empirically grounded with survey data have been used extensively, this is not the case for the energy domain. Most research in energy consumption behaviour uses some form of empirical data for model parametrization, but some lack individual-level data from surveys. Even if individual-level data is available from surveys, some publications still opt for random functions or constants for consumer attributes (Chapuis et al., 2022). There are opportunities here to integrate data in a proper way, and it is unknown what that means for the attitude-behaviour gap. There exist novel methods such as combinatorial optimization for synthetic population generation based on survey data, that could prove beneficial to research in this area. This is especially important considering the main research question, the personal attributes of households have been shown to be significant indicators of energy consumption behaviour in existing research.

3 Research Objectives

The purpose of this chapter is to introduce the research objectives based on the knowledge gap identified earlier. These objectives lead to the research question that will be addressed in this research. Subsequently six sub questions are introduced that help to address the main research question, with an in-depth discussion of the sub questions available in Appendix B.

3.1. Research Objectives

The problem context is the presence of an attitude-behaviour gap in Dutch household energy consumption. Consumers are not rational in their choices, and psychology and behavioural economics show there exists an asymmetry between consumers' attitude and their decision-making behavior, leaving petajoules of potential energy savings on the table every year. The attitude-behaviour gap has been studied, but aside from a list of potential explanations it is not clear exactly how it is shaped and what factors cause it to emerge. Modelling efforts have been made with varying degrees of rigour and success. The contributions of this research are multifold: (1) the development of an empirically grounded ABM with theoretical foundation to analyze solar PV diffusion in a heterogenous population of households in The Netherlands, (2) description of the system and model in fine detail in terms of technological, social, behavioural, economic and environmental aspects at a low system level, (3) implementation of a more appropriate synthetic population initialization method based on individual-level survey data, (4) implementation of a small-world social network refined with agent attributes such as income class and education, (5) application of the model in ex-ante policy intervention exploration for evaluating policy impacts to judge their effectiveness on increasing the adoption rate of household solar PV.

3.2. Research Question

Based on the research objectives and knowledge gap discussed in the previous chapter, this research aims to explore the attitude-behaviour gap in a household energy consumption context. An empirically grounded ABM approach with theoretical foundation will be used to study household decision-making, with the goal of understanding what factors may cause the attitude-behaviour gap of diverse individuals. Ultimately, to close the gap by lowering the barriers to adoption with policy interventions. Based on the identified research objectives the following research question is posed:

To which extent can different psychological factors influence the emergence of the attitude-behaviour gap in household energy consumption, and what policy interventions can be employed to close the gap?

The research question will be answered with an ABM simulation model supported by individual-level survey data on household behaviour regarding energy efficient technology investments.

3.3. Sub Questions

This section introduces the six sub questions that contribute towards addressing the main research question posed in the previous section. The sub questions guide the modelling cycle and will be addressed throughout the following chapters. The detailed research activities, research tools used, and deliverables used to address the sub questions are discussed in-depth per sub question in appendix B. The list of sub questions is displayed below:

SQ1: What factors are relevant in exploring the emergence of the attitude-behaviour gap?

SQ2: To what extent are these factors captured in the survey data?

SQ3: How can these factors be represented in an agent-based model?

SQ4: To what extent does each identified factor contribute towards shaping the attitude-behaviour gap?

SQ5: What are policy interventions that can contribute towards closing the attitude-behaviour gap, and what is their effectiveness?

SQ6: How can the results of this study aid policymakers in closing the attitude-behaviour gap?

4 Research Design

This chapter presents the exploratory simulation modelling approach chosen to address the main research question, and the limitations of the approach that must be considered and dealt with. The contributions of this research are discussed, in addition to the methods chosen to complete the research phases. The research approach has been based on existing ABM frameworks, and the weaknesses of the ABM method have been addressed. Policy scenarios will be the foundation for exploring the effectiveness of policy interventions, the design of these experiments and scenarios is discussed in the last section.

4.1. Research Methods

Various research methods are used throughout different phases, resulting in deliverables, and addressing the sub questions. In the first phase desk research and a literature review are conducted to give a broad overview of core concepts and to position the research in the theoretical background, to evaluate what the current developments and shortcomings are around the topic. Secondly, the model is conceptualized, and a detailed model design is created, then the model is built iteratively based on the insights from the first phase. In this step the statistical data processing of the quantitative survey is also conducted. Subsequently the model evaluation takes place, model verification and validation are conducted, experiments are run, data analysis is performed, and data is visualized. Ultimately in the last phase, the key insights from the simulation model are reported and discussed to conclude and offer policy recommendations. The way these research methods, phases, deliverables, and sub questions intertwine is visualized in the research flow diagram displayed below. The order of tasks is shown from top to bottom.

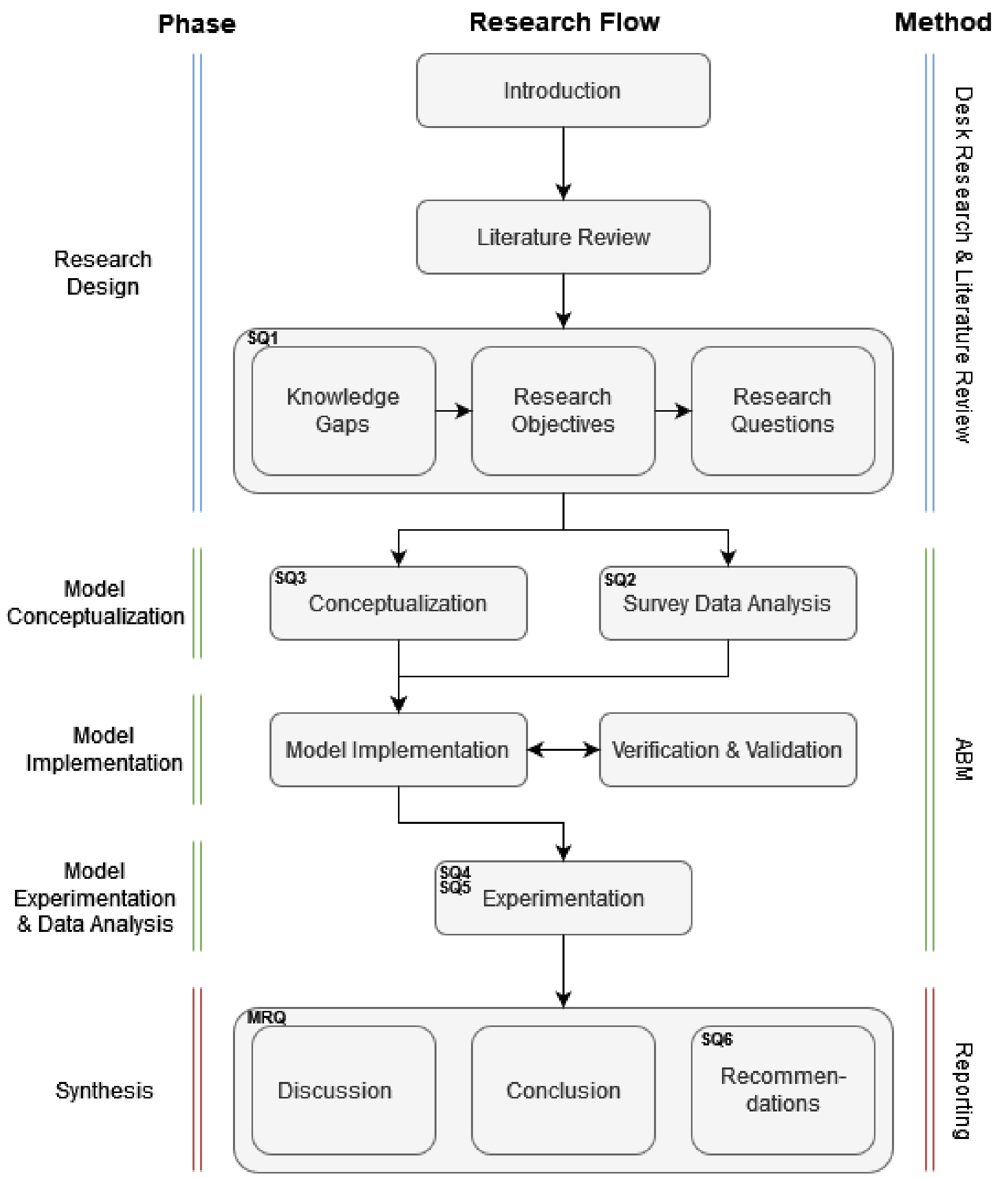


Figure 3

Research Flow Diagram indicating phases, research flow, method, sub questions (SQ1-SQ6), and main research question (MRQ).

4.2. Data

Using ABM without following established modelling principles such as empirical model initialization offers no advantage over using other modelling paradigms. Input parameter values from survey data offer a strong empirical foundation and ensures the model is properly calibrated. This research uses a survey questionnaire designed by Leila Niamir and is used in a series of publications (Niamir et al., 2020), the survey was conducted in 2016 in Dalfsen, Overijssel. The survey data contains individual-level data on Dutch households (n=1035) on a wide range of topics related to energy consumption, while simultaneously carrying out the model calibration (Fagiolo et al., 2006). The survey data is used for parametrization of agent personal characteristics, dwelling characteristics, and social network parameters. A deeper analysis of the survey data design, descriptive statistics, probit regression analysis, and consequent parametrization can be found in section 5.3. A synthetic population of household agents are initialized using the combinatorial optimization (CO) approach (refer to section 5.5). This method generates a synthetic population from a sample of individual-level survey data and matches the marginals of this sample to the Dutch population using a hill-climbing algorithm. The process of choosing values for the parameters present in the model is situationally dependent. The values of the parameters come from various sources. From most to least preferred the sources are survey data, recent CBS data, similar literature, based on assumption, or the modellers' informed decision.

4.3. Model Design

A common simulation modelling methodology for developing ABMs of socio-technical systems is used as basis for this research (Chappin et al., 2019; Nikolic & Ghorbani, 2011; Van Dam et al., 2013). This study aims to analyze the attitude-behaviour gap and the barriers to adoption that lead to suboptimal diffusion of energy-efficient technologies, specifically household solar PV, in order to better understand and subsequently close the gap. The socio-technical system (STS) consists of a social network of actors and a physical network of technical artefacts (Van Dam et al., 2013), in this case particularly producers and consumers of energy and households that are physically connected to the energy system. Considering this perspective and problem context an approach that includes both social infrastructure and technical infrastructure, and their interrelation, is required. This is achieved with the agent-based modelling paradigm.

The ABM development approach taken here does not differ significantly from other approaches illustrated by Nikolic & Ghorbani (2011) or Van Dam et al. (2013) or Chappin et al. (2020), with the only exception being the participatory stakeholder involvement. The survey data is used to provide specifics on barriers, technologies, and households. The survey that offers the empirical foundation for the simulation model has already been conducted, this limits the model scope somewhat. Instead of the traditional approach where participatory stakeholder involvement is used for the system analysis and leads to identifying additional components and empirical evidence necessary to get a complete image of the system, in this research approach the model must be built around the existing survey data.

A simulation modelling approach will be used to simulate a synthetic population consisting of heterogenous households parameterized by real-world survey data. Decision-making is implemented at a household level based on the Theory of Planned Behaviour (Ajzen, 1991). Households interact with one another by sharing information and opinions regarding solar PV in a small-world social network connecting the households. Every timestep, households choose whether to invest in energy-efficient technologies depending on the environmental, economic, and social utility. As more and more households adopt solar PV the diffusion of the technology throughout the population can be monitored and analyzed. A more detailed model formalization can be found in chapter 6.

The model can be used to explore the barriers to adoption that stop consumers from investing in energy-efficient technologies thereby limiting their adoption rate, the very same barriers that are responsible for creating the energy-efficiency gap. By simulating the barriers to adoption and decision-making process of households, effective interventions can be tested. Ex-ante policy intervention exploration is valuable to evaluate policy impacts to judge their effectiveness. The results of this study can aid policymakers in reaching informed decisions regarding higher energy-efficient technology adoption rates and understanding consumer behaviour in general.

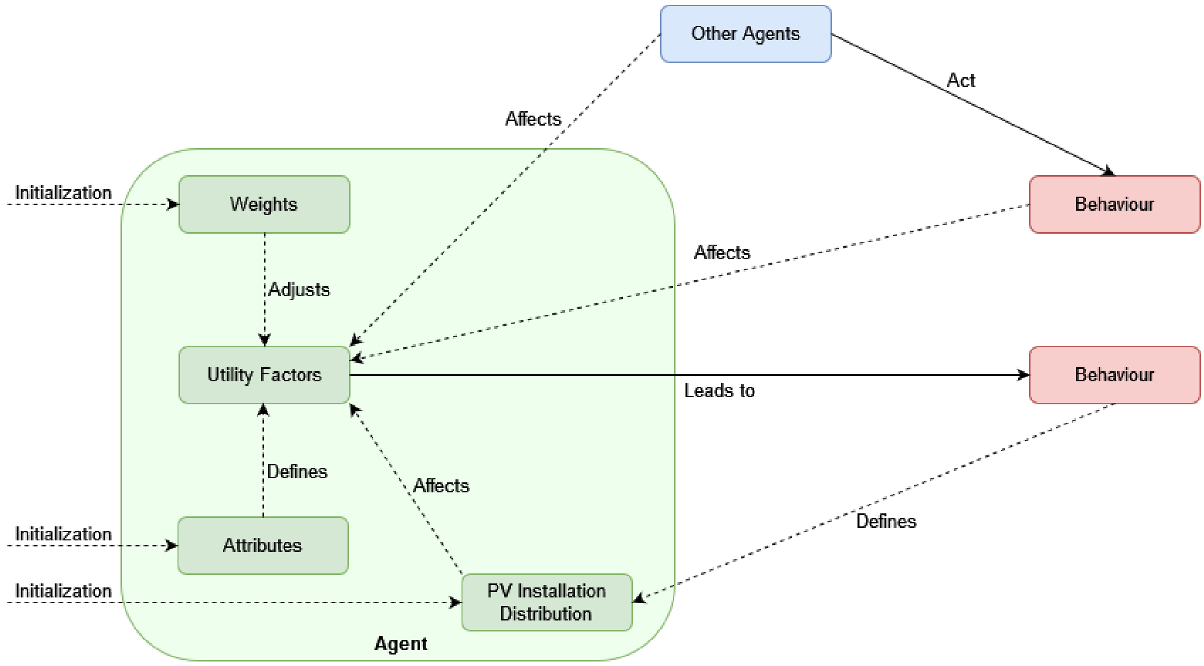


Figure 4
Model architecture diagram displaying variables and their relationships.

4.4. Experimental Design

The exploratory nature of the research means the experimental design consists of a wide variety of different input parameters and various policy interventions. ABM lends itself well to the exploratory approach, and rather than running a limited set of experiments the model is run many times to systematically explore the parameter space (Van Dam et al., 2013). Before this is done, a first experiment is run to investigate the diffusion process. The overall goal of the experimental design is to show the emergence of the attitude-behaviour gap, determine what factors contribute towards the emergence of the gap, identify what the barriers to adoption are, and ultimately explore policy interventions that may aid in closing the gap by targeting these barriers to adoption. The parameter settings are different for every experiment and can be found in table 2. The parameters that remain the same may be found in appendix D. Each experiment is executed 100 times to explore the spread between repetitions.

In the first experiment (E0) the parameters are fixed to investigate the diffusion process and the emergence of the attitude-behaviour gap. A very long time horizon is used to see whether and when the diffusion process diverges. This preliminary analysis of the parameter space allows a time horizon to be determined for the remaining experiments.

The second experiment (E1) consist of a large number of scenarios that are run to analyze the model behaviour and the emergence of the behaviour-attitude gap under varying initial conditions. In order to identify to what extent different psychological factors contribute towards the output variance in the diffusion rate, a *global sensitivity analysis* (GSA) is performed to effectively sweep the parameter space. This experiment investigates how psychological factors influence the diffusion process and the emergence of the attitude-behaviour gap, to address sub question 4 and the main research question.

When it is clear what the barriers to adoption are from the second experiment, the third experiment is executed. Here the goal is to investigate what policy interventions can contribute towards closing the attitude-behaviour gap and what their effectiveness is, to address sub question 5 and the main research question. Firstly, two base case scenarios with realistic input parameters are modelled. One scenario with no policy interventions (E2) and another scenario with the current Dutch policy landscape (E3). The rate of diffusion in this scenario acts as case to which scenarios with additional policy interventions can be compared. Subsequently the policy interventions may be explored, to address sub questions 5 and 6.

The first policy intervention is not a proposed intervention, instead it is an already existent one. A policy named the *salderingsregeling* has been introduced into the Dutch Elektriciteitswet of 1998 (RVO, 2017). The *salderingsregeling* is a feed-in tariff aimed at small-scale users to stimulate adoption of solar PV technology by making it more economically attractive for adopters[2]. There was a controversial proposition by policymakers to phase-out the current *salderingsregeling* in 2021 (Tweede Kamer der Staten-Generaal, 2020) but no actions were taken. The current Ministry of Economic Affairs and Climate Policy announced plans to reopen the discussion again. The proposed phase-out would gradually reduce the amount of electricity households can supply back at full price, from the current 100% to 0% in 2031 (see table 1). However, the return fee is still a point of discussion and minister Jetten for Climate and Energy supports setting the return fee at 80% of the households' electricity price. This is a very relevant topic considering the current discussion around the topic, to consider what the potential effects of phasing out the *salderingsregeling* are on the adoption of solar PV installations. Therefore, three scenarios are explored in this experiment, the phasing out of the *salderingsregeling* with no return fee (E4a), a second scenario where the *salderingsregeling* is phased out but an 80% return fee remains in place (E4b), and a third scenario with instant discontinuation of the *salderingsregeling* (E4c).

Table 1
Proposed plan to phase-out the salderingsregeling (Tweede Kamer der Staten-Generaal, 2020).

Year	2022	2023	2024	2025	2026	2027	2028	2029	2030	2031
Phase-out percentage	100%	100%	100%	64%	64%	55%	46%	37%	28%	0%

Furthermore, the effects of rebates are explored. Currently, households and small businesses in The Netherlands have the right to a tax rebate when investing in solar PV installations for the first time

[2] At the end of each year, households with solar PV installations can take the energy bill for their electricity consumption and cancel out (in Dutch: *salderen*) their consumption with the electricity they generated and supplied back into the distribution network. It ensures that households with solar PV are reimbursed for the electricity they generated and did not consume themselves—but instead supplied it back into the distribution network—at the market price of electricity. If a household supplies more than they consume, they get reimbursed with a return fee, generally around €0.09 per kWh (Milieu Centraal, 2022), depending on their energy contract. So, households receive full price for electricity they generate and supply back, capped at the level of their own consumption, and receive a lower return fee if they generate and supply more than that level of consumption.

(Rijksoverheid, 2022). This tax rebate is equal to the BTW-value of 21% of the total installation price, and drastically reduces the payback period of solar PV installations in The Netherlands and the high upfront cost normally associated with solar PV installations. This experiment explores possible future scenarios where this tax rebate is halved (E5a) or discontinued completely (E5b).

Considering the current energy crisis in Europe due to the invasion of Ukraine, experiments with high energy price are executed. A range of prices from the historic price of 2021 (CBS, 2022a) to the current price of approximately 0.77 €/kWh (Essent, 2022) is considered in experiments (E8a-e). These experiments are added to evaluate the robustness of policy interventions in extreme situations.

Table 2
Experimental design table.

Experiment	Label	Parameter	Value
Preliminary investigation	E0	none	-
Contribution towards the attitude-behaviour gap	E1	PBC_factor w_env_scaling w_eco_scaling w_soc_scaling tpb_eco_unc_mean tpb_eco_unc_stddev	[-1, 1] [-3, 3] [-3, 3] [-3, 3] [0, 1] [0, 0.2]
Base case A	E2	tax_rebate salderingsregeling	off off
Base case B	E3	tax_rebate salderingsregeling	21% constant
Salderingsregeling phase-out	E4a-c	salderingsregeling	[phase-out, phase-out 80% lower bound, off]
Tax Rebate discontinued	E5a-b	tax_rebate	[10%, 21%]
High energy price	E6a-e	electricity_cost	[0.2, 0.3, 0.4, 0.5, 0.6]

5 Conceptualization

In this chapter the conceptualization of the system and the model formalization are presented. Since the focus is on consumer behaviour and the emergence of the attitude-behaviour gap, the demand side consisting of a sample of households and their decision-making behaviour is thoroughly discussed. Firstly, the actions that may be undertaken by the households and the operationalization of the theory of planned behaviour are considered. Secondly, the statistical analysis of the survey data is performed. Lastly, the components of the system that must be modelled, but are not the focus of this research, are discussed. These components may be stylized, simplified, or exogenous variables. Simultaneously the assumptions, choices, and justification thereof are presented.

These topics are examined by studying the established literature, and subsequently discussed in terms of agents, their actions, the environment, and their relationships. The sub questions that are addressed in this chapter are:

SQ1: What factors are relevant in exploring the emergence of the attitude-behaviour gap?

SQ2: To what extent are these factors captured in the survey data?

5.1. Consumer behaviour

In the model households are represented by agents, who may or may not adopt energy-efficient technologies depending on their environment and personal attributes. The emergent pattern in focus is the attitude-behaviour gap. Firstly, the consumer actions are discussed, these actions represent what the agents can do. Secondly, the TPB operationalization is considered, households have certain characteristics (income class, age, gender) that influence their personal attitudes and subjective norms, that subsequently govern their decision-making process.

5.1.1. Consumer actions

First and most relevant to the model is the consumer behaviour. The behaviour most relevant to this research is the decision-making process of energy consumers, specifically households. The actions the consumers take affect the emergent pattern, the diffusion of energy-efficient technology. In reality consumers can decide to take various actions to improve their energy-efficiency in order to lower their CO2 footprint, they may (1) switch energy provider to one that delivers greener energy, or (2) change their habits to be more conservative, or (3) invest in innovative energy-efficient technologies. Since the model is of the 'diffusion of innovations' archetype only the investment in innovative energy-efficient technologies is considered, specifically solar PV. Other actions are disregarded. Generally, diffusion models only consider the investment into energy-efficient technologies and their diffusion amongst the population (Rogers, 2010).

The decision-making of the households is key to the rate of diffusion, if there are no barriers to adoption in the decision-making process the technology can diffuse at optimal rates throughout the population. This process is emphasized by the bottom-up approach of ABM and the agents' individual choices lead to cumulative consequences (Muelder & Filatova, 2018). Not all households can choose to adopt solar PV. Before the model run (during initialization) a selection of households is chosen to have already adopted solar PV in the past, and therefore cannot choose to adopt solar PV again. This initial percentage of households with solar PV is user defined and adjustable, with a default value of 20%. Determined by dividing the total number of solar PV installations (CBS, 2022d) by the amount of residential households in the Netherlands (CBS, 2022c). The fraction of households that are able to adopt solar PV, do so based on the operationalized theory of planned behaviour discussed in the next section.

5.2. TPB Operationalization

The consumer behaviour is decided by the decision-making process of individual agents. Together the choices of these agents aggregate into the macro-level behaviour such as the adoption rate of new technologies. For diffusion simulation ABMs it is strongly advised to structure the agent decision-making process based on psychological research that is supported by empirical evidence, because it provides a rigorous framework (Moglia et al., 2017). Indeed, the way ABMs implement human decision-making is often based on a theoretical foundation, but there is no universally accepted and objective choice of theory (Chappin et al., 2019; Schlüter et al., 2017). There have been many attempts at shaping psychological theories that can explain or predict human decision-making. For this research the theory of planned behaviour by Ajzen (1991) is chosen. It is widely used in a variety of areas where behaviour and more specifically human decision-making plays a role, and it is widely represented in the literature review and also in other literature reviews (Hesselink & Chappin, 2019; Jackson, 2005). TPB is chosen because it incorporates different behavioural factors that are relevant for energy consumer behaviour, and it is relatively easy to operationalize (Hesselink & Chappin, 2019).

The theory suggests that a person's intention to engage in certain behaviour is determined by three factors: (1) personal attitude, (2) subjective norm, and (3) perceived behavioural control (PBC). The diagram below (figure 5) depicts the simplified TPB components and relationships between them. The components are discussed individually in the next subsections.

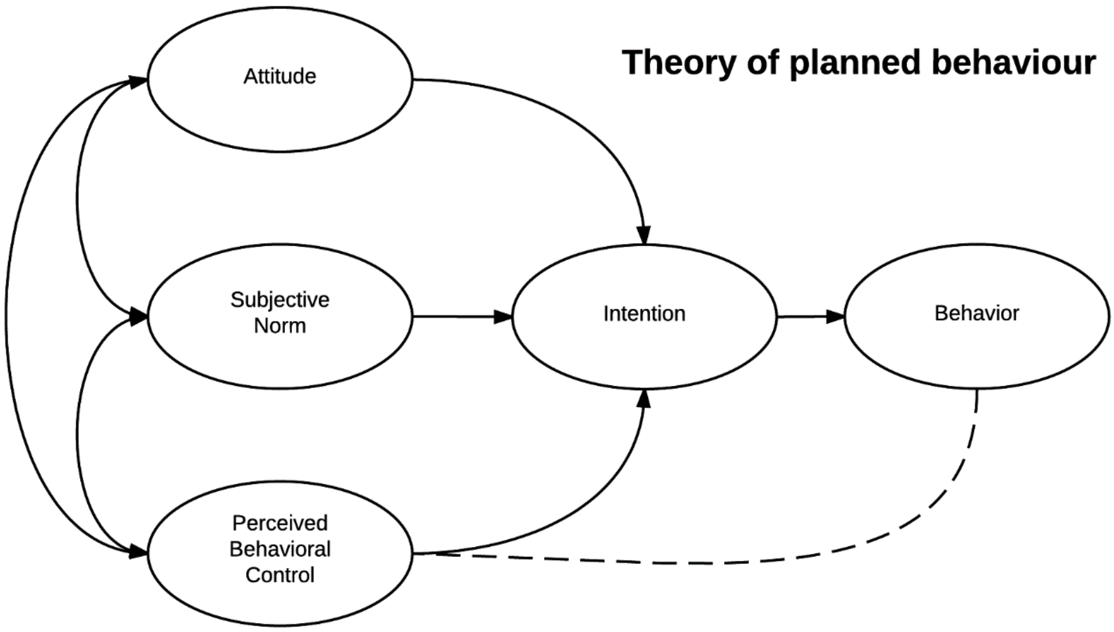


Figure 5
TPB as described by Ajzen (Ajzen, 1991).

The methodological challenge here is the operationalization of TPB. There is no objective method of implementing the theory, so it remains rather subjective (Muelder & Filatova, 2018). The framework remains the same but there are subtle differences between implementations. It is not the scope of this research to compare & contrast different TPB implementations, instead the research by Muelder & Filatova (2018) is used as reference. In the article, different implementations of TPB are analyzed and compared, with results showing significant differences in output variables between different implementations. The major difference between the implementations that are compared is the operationalization of the PBC component. Based on these results the base version of TPB (named *MF ABM* after the authors) is chosen as the decision-making process for the households in this model. Their implementation displays lower sensitivity to exogenous architectural parameters compared to the other implementations (Muelder & Filatova, 2018). The implementation by Muelder & Filatova (2018) is designed based on factors elicited from a participatory workshop in Dalfsen, which considered the adoption of solar PV. This ensures that technology specific factors only relevant for solar PV are included in the operationalization.

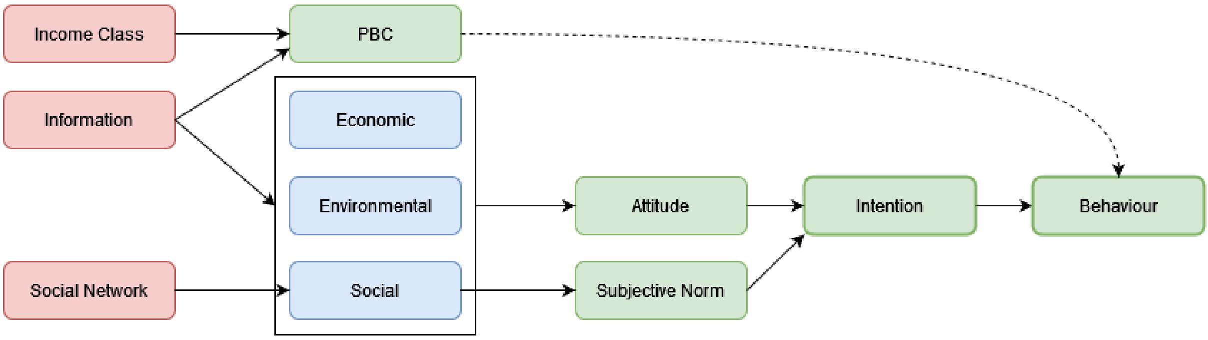


Figure 6
Architecture of the TPB operationalization displaying the decision-making for solar PV adoption of an agent.

The architecture of the agent decision-making is shown in figure 6. Information from other agents in the model or personal characteristics (shown in red) influence the utility factors of agents shown in blue. These ultimately influence the TPB components (shown in green) that lead to the behaviour of an agent, whether they adopt or do not adopt solar PV. Section 6.1 features an in-depth discussion on the model flow.

One important caveat is the static nature of standard TPB, it is not specified how these components evolve over time, while in reality norms and attitudes evolve over time (Rai & Robinson, 2015). This means the model should include a method of dynamically evolving the TPB components of the households. Agents have static heterogenous preconceived weights originating from the survey data, that alter the importance of certain utility factors in their final choice, but the utility factors themselves are dynamic. This also has implications for the agents, since the utility functions are dynamic, the option is relevant to the current timestep only. There is no way for agents to foresee if possible choices in the future are better than the choices currently presented to them, the information the agents have is imperfect.

5.2.1. Attitude & Subjective Norm

TPB distinguishes between attitudes and personal norms. Personal attitudes consist of our knowledge, attitudes, and biases. Subjective norms consider our perception about the attitude of others, the perceived social pressure to perform an action or not, for instance our perception of social expectations or social pressure are subjective norms (Ajzen, 1991). However, the operationalized form often merges the two in a multi-attribute utility function (Muelder & Filatova, 2018).

The attitude represents a mixture of context-dependent factors such as payback period and personal CO2-emission savings compared to the average. The assumption is made that subjective norm is one of the three decision factors (economic, environmental, and social) that are important for the households' intention (Muelder & Filatova, 2018). Unlike the TPB implementation by Muelder & Filatova (2018), in this research the comfort factor is not considered because it could not be empirically grounded. The comfort factor represents aesthetics and pride in owning a solar PV installation, aspects that are not represented in the survey data, therefore the comfort utility factor is omitted. The three utility factors are discussed below, their values may range between 0 and 1.

Firstly, the environmental factor (equation 1) compares CO2-emission savings between two values, the emissions saved by the household s_{pv} and the average emissions savings s_{avg} for solar PV, which

CBS states to be 0.676 ktonne per kWh (CBS, 2009). The variable s_{pv} is endogenous and is different for each agent, depending on the technical aspects of their proposed solar PV installation. Variable k represents the environmental awareness factor that is adjusted by information-based policy interventions.

$$u_{env} = \frac{e^{(s_{pv}-s_{avg})}}{(k+e^{(s_{pv}-s_{avg})})} \qquad (1)$$

Secondly, economic factor (equation 2) is dependent on the payback period of the solar PV investment. If the decision to adopt solar PV is economically viable for a household, the economic factor is higher. The lifetime of the panels t_{pv} is set at 25 years. The payback period t_{pp} is determined by equation 3 representing the time required for the cumulative revenue r_{pv} to be larger than the initial solar PV cost C_{pv}.

$$u_{eco} = \frac{(t_{pv}-t_{pp})}{t_{pv}} \qquad (2)$$

$$t_{pp} = t(C_{pv} < r_{pv}) \qquad (3)$$

Lastly, the influence of subjective norms is considered, in the form of social utility. The subjective norm is implemented as the share of households in the social network that have already adopted the technology. The social factor is based on the social network of the household (refer to section 5.4 for social network conceptualization). The households are connected in a network and can only communicate along the edges that represent social connections. A comparison is made between the number of neighbors in the network that have already adopted solar PV n_{ado} and the total amount of neighbors in the network n_{tot}. Furthermore, the edges are weighted based on the age, education, and income parity between the two households (see equation 12).

$$n_{ado} = (w_1 n_1 + w_2 n_2 + \cdots + w_k n_k) \qquad (4)$$

$$u_{soc} = \frac{n_{ado}}{n_{tot}} \qquad (5)$$

5.2.2. Perceived Behavioural Control

The perceived behavioural control is our belief of the extent to which we can control our behaviour, similar to self-efficacy or locus of control seen in other psychological theories. This can be both internal (determination, own ability) or external (resources, available support). If we believe to have a higher level of control over a situation, we are more likely to exert more effort to succeed (Jackson, 2005). Perceived behavioural control is a general concept and may include financial, knowledge, and time constraints. However, as the perception of affordability is often the most significant barrier to adoption (Rai & Beck, 2015; Rai & Robinson, 2015) only the financial aspect is included in the PBC component. When households are in a more comfortable economic position the barrier to adoption is lower. A simple payback period is the metric used by households to see whether the investment decision is in their favor, but this is only considered if the affordability barrier is passed. This choice is a point of discussion because it is not quite clear where the PBC barrier should be set—what should and what shouldn't be included—but ultimately a choice must be made (Muelder & Filatova, 2018). Future research could expand the PBC component in the model to cover more constraints besides financial.

In the original theory of planned behaviour Ajzen (1991) argues that the PBC can be taken as an indicator of actual behavioural control. However, in this research PBC directly influences the behaviour because the 'actual behavioural control' component is omitted. The PBC is largely dependent on one's actual control over a situation (Muelder & Filatova, 2018), so both are equal for this purpose. Jackson (2005) agrees that if the individual's perceptions are not misguided the PBC is likely to indicate actual behavioural control. If a person has the willpower over their own actions then intention is likely closely related to behaviour (Jackson, 2005).

Note that TPB suggests that a person's *intention* to engage in certain behaviour is determined by the attitude and subjective norm components, not the actual behaviour itself. PBC should moderate the relationship between intention and action, but in the model, this is only achieved indirectly. PBC is determined first so a computationally expensive multi-attribute utility function can be estimated for a smaller fraction of households, here PBC is acting as a filter (Muelder & Filatova, 2018). PBC can be modelled as a threshold or cut-off value, or probabilistic. In this model both implementations are present, if the probabilistic option is chosen PBC serves as a probabilistic barrier between intention and behaviour, where the intention to adopt is more likely to result in actual behaviour if the financial situation (and thus PBC) is better, accurately representing reality where households with higher income are more likely to consider the decision to adopt solar PV (Ameli & Brandt, 2015). If the threshold option is chosen, the PBC barrier represents a threshold value that must be passed (equation 8).

The probabilistic income barrier is represented by a sigmoid function (equation 6), compared to a uniformly random value r between 0-1 (equation 7). Where n is the average household income class that normalizes x which is the specific agents' own income class, and with scaling parameter λ set to 1.

$$PBC_i = \frac{1}{1+e^{-\lambda(x-n)}} \tag{6}$$

$$PBC_i > r \qquad \{r \in \mathbb{R} \mid 0 \leq r \leq 1\} \tag{7}$$

The PBC income barrier may be toggled off, or the probabilistic test may be replaced by a user defined threshold value T_{PBC} (equation 8).

$$PBC_i > T_{PBC} \tag{8}$$

5.2.3. Intention and Behaviour

Ultimately, to link the TPB components to behaviour a multi-attribute utility function is used. For every agent the three context-dependent factors (financial, environmental, and social) shape their attitudes and subjective norms, which in turn determine the behaviour of agents. These context-dependent factors contribute to the households' overall utility in a weighted sum, with the heterogenous static weights derived from the statistical analysis of the survey data. Households calculate two individual multi-attribute utility functions, one for each action, adopting or maintaining the status quo (not adopting solar PV). Households then choose the maximum of the individual multi-attribute utility functions and take the corresponding action.

Since the utility functions are dynamic, the option is relevant to the current timestep only. There is no way for agents to foresee if possible choices in the future are better than the choices currently presented to them, the information the agents have is imperfect. Meaning the agents are boundedly-rational and the utility maximization is myopic (Muelder & Filatova, 2018).

PBC should moderate the relationship between intention and action, but in the model, this is only achieved indirectly. The multi-attribute utility function (equation 9) is only calculated when the probabilistic PBC barrier (equation 7) is passed. This reverse order does not affect the results but does reduce the computational overhead. If the probabilistic PBC barrier is passed, the utility for both decisions (not adopting or adopting) is determined and the choice with maximum utility is performed.

$$U = w_{eco} * u_{eco} + w_{env} * u_{env} * + w_{soc} * u_{soc} \qquad (9)$$

5.3. Survey data

The aim of this section is to analyze the data that offers the empirical foundation for the model. The need for a strong empirical foundation was already highlighted in the literature review and identified as the first knowledge gap. An empirical survey that provides input parameters for the households provides a strong empirical foundation for the model development (Maya Sopha et al., 2011), while simultaneously carrying out the model calibration (Fagiolo et al., 2006). At the end of this section the second sub question is addressed.

5.3.1. Survey Design

The survey questionnaire is designed by Leila Niamir and is used in a series of publications (Niamir et al., 2020) and contains five sections with a wide variety of questions per section:

1. Sociodemographic characteristics;
2. Dwelling characteristics;
3. Energy consumption, behaviour, and sources;
4. Personal attitudes and opinion;
5. Social networks.

The survey questions vary in nature and the responses are different per question, they can be multiple choice for categorizations such as house type, Likert-scale and semantic differential for questions regarding attitudes and opinions, or open-ended. Producing mixed data with different levels of measurement: ratio, interval, ordinal, and nominal. The questionnaire features both a Dutch and Spanish group of respondents, but only the Dutch group (N=1035) is considered for this research because this research is focused on Dutch households.

During survey construction Niamir et al. (2020) guaranteed the quality of the questionnaire by carefully considering the wording of questions and response scales to reduce response bias and social-desirability bias.

> "While interpreting any survey results, the possibility of a response bias should be considered. The wording of questions and response scales, as well as the respondents' tendency to answer questions untruthfully, particularity for behavioral factors when they may feel pressure to give socially acceptable answers, can all contribute to a response bias. To minimize the chance of response bias, our survey took a 3-fold approach by assuring cross-questions, validation by an interdisciplinary team of experts (e.g., psychologist, energy economist, sociologist, governance and policy expert, statistician) and by conducting pilot studies. In particular, to improve the survey quality and feasibility, we performed three pilot studies with: (a) a team of international experts (19 colleagues in the Netherlands and Spain); (b) a small sample of households in Overijssel; (c) a small sample of households in Navarre. The feedback from these pilots was integrated in the final questionnaire to increase its quality and the comprehension of questions by various participants." (Niamir et al., 2020, p. 3)

In the following section a descriptive analysis of the survey data is presented, here the socio-demographic characteristics of the survey sample is shown and compared to the macro-level data of the target population. Subsequently the statistical analysis is performed.

5.3.2. Survey Data Descriptive Analysis

The survey data indicates that there are significant differences between the survey sample and the target population. The survey is conducted in Dalfsen, Overijssel, a relatively rural area in The Netherlands that is not part of the Randstad. While most characteristics are relatively similar when compared, the average age of the respondents is much higher than the average of the Dutch population and the education level is lower. Despite the lower education level the average annual incomes between the sample and the Dutch average is relatively similar. The large majority of respondents lives in a house instead of an apartment, and 71% of respondents bought their house. The majority of respondents are not aware of the energy label of their house. Tables 3-5 below display the descriptive analysis of the survey data.

Table 3
Socio-demographic distribution of the survey sample and The Netherlands.

Characteristic	Survey sample	National (The Netherlands)	Source
Population	1035	17.4M	(CBS, 2021c)
Male population (%)	54%	49%	(CBS, 2021c)
Average income (k€/year)	72.7% in group 2 and 3 (10 to 50)	34.0	(CBS, 2021b)
Average age	58.8	42.3	(CBS, 2021c)

Education level (%)	Primary	3	7.7	(CBS, 2021a)
	Secondary	49.6	18.1	
	Tertiary	21.6	37.9	
	Bachelor's	14.6	22.1	
	Master's	9.6	13.4	
	Doctoral	1.5	-	

Table 4

Personal characteristics of survey respondents.

Personal characteristic		**Survey sample**
Gender (%)	Male	53.6
	Female	46.4
Average age		58.8
Education level (%)	Primary	3
	Secondary	49.6
	Tertiary	21.6
	Bachelor's	14.6
	Master's	9.6
	Doctoral	1.5
Employment status (%)	Employee (full-time & part-time)	57.8
	Self-employed	9.4
	Unemployed	14.2
	Homemaker (housewife/husband)	3.2
	Retired	5.6
	Student	9.1
	Other	0.5
Annual income (%)	<10k	11.4
	10k-30k	46.8
	30k-50k	27.8
	50k-70k	8.7
	70k-90k	3.0
	90k-110k	0.9
	>110k	1.3
Economic comfort status (%)	Very difficult	10.2
	Difficult	20.9
	Coping	48.6
	Living comfortably	16.2
	Very comfortably	4.2

Table 5
Dwelling characteristics of survey respondents.

Dwelling characteristic		**Survey sample**
Residence type (%)	Apartment	14.9
	House	85.1
Tenure (%)	Own	71
	Rent	29
Residence size (%)	<50m^2	4.5
	50m^2-100m^2	35.7
	101m^2-150m^2	35.7
	151m^2-200m^2	15.2
	>200m^2	8.9
Residence age (%)	<5y	4.4
	5y-10y	7.4
	11y-20y	15.8
	21y-35y	26.1
	36y-50y	25.4
	>50y	20.8
Energy label (%)	A	15.7
	B	15.9
	C	11.7
	D	4.6
	E	4.6
	F	4.0
	Don't know	43.5

5.3.3. Survey Data Statistical Analysis

The operationalization of the theory of planned behaviour includes three utility factors that influence the behaviour of households. These context-dependent factors contribute to the households' overall utility in a weighted sum, with the heterogenous static weights derived from the statistical analysis of the survey data. In order to define these weights, the survey questions that shape these factors had to be determined. Ideally this occurs the other way around, but this reverse order of operations had to be taken because the survey was already conducted. Initially, groupings of roughly five questions were formed that shaped the utility factors, but this led to several issues: (1) questions are selected subjectively, (2) not all questions showed significant correlation to the intention to invest in solar PV, and (3) the survey questions were all weighed equally while some are more influential than others. These grouping of the survey questions is presented in appendix C. To address this issue, probit regression is performed to select the single survey question that best represents the specific utility factor.

$$P(X) = \Phi(\beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_k X_k) \qquad (10)$$

The binary probit regression model is closely related to logistic regression, it is designed to fit a regression model where the dependent variable is an event with two possible outcomes, in this case the discrete choice between adoption of solar PV or no adoption. The probability of solar PV adoption is related to predictors (equation 10), and the fitted model may be used to make predictions.

The survey questions that best represent the utility factors are chosen from the grouping of survey questions (appendix C) based on statistical significance (p-value). The survey questions from the groupings that showed the highest correlation to the choice of installing solar PV are shown in the table 6. These survey questions are the foundation of the weights for the utility factors.

Note that the intention of the respondents is measured by the question: "*When did you apply your energy production (e.g. install solar panel/solar thermal/turbines) or do you plan to apply it?*". Initially, the responses to this question were not binary; respondents could choose between four responses: (1) more than 6 years ago, (2) in the past 5 years, (3) in the coming year, and (4) in the next 3 years. In SPSS the responses to this question are recoded into a binary variable, with the former two categories corresponding to 0's and the latter two categories corresponding to 1's. This is done to separate past behaviour from intention, or in other words, expected behaviour.

Table 6
TPB utility factors and related survey questions.

Type	Factor	Label/Question	Scale	p-value	Exp(B)
Independent	Environmental	My energy source choice (renewables or fossil fuels) has an impact on the environment	Likert	0.002	1.245
Independent	Economic	If there were subsidies, I would produce part of my green energy consumption (e.g. install solar panel or fund a wind turbine)	Likert	0.001	1.511
Independent	Social	I would reduce my energy consumption if more practical information on how I can invest in green energies (e.g. install solar panels) would be available	Likert	0.002	1.168
Dependent	Intention	When did you apply your energy production (e.g. install solar panel/solar thermal/turbines) or do you plan to apply it?	Binary	-	-

The three utility factors correlate positively as shown in table 7. The highest correlation is seen between the social and economic factors, while the others (env-soc, env-eco) are less substantial. The social and economic factors display a correlation almost three times higher, underlining a strong connection between the social networks and economic situation of households. At earlier stages of the model a comfort utility factor was included but this was eventually removed because no direct empirical data to support this factor could be found in the survey data.

Table 7
Pearson correlations between the utility factors.

Variables	Env	Eco	Soc
Env	1	0.19	0.15
Eco	0.19	1	0.45
Soc	0.15	0.45	1

5.4. Social Network Diffusion

The social network governs the flow of information between agents. It can be viewed as a set of relationships (edges) that connect the agents (nodes) in a network structure. Research demonstrates that social dynamics such as communication are related to the diffusion of solar PV systems (Jager, 2006; Maya Sopha et al., 2011; Shum, 2010), therefore it must be included as a model component. The varying degrees of complexity and rigor in which agents communicate with one another is very model dependent. For this research the aim is to create a small-world networks where connections are adjusted based on characteristics—in this case income class, age, and education—resulting in more realistic clustering and degree distributions. Including these important social aspects will result in a more representative model.

Most commonly 'small-world networks' (Watts & Strogatz, 1998) are used to represent how information can flow between households (Amblard et al., 2016), with nodes being the households and edges the communication channels. In small-world networks, households interact with their local neighbors and with a random fraction of the population forming non-local connections that represent family, friends, or relatives. Since energy-efficient technologies such as solar PV and hybrid vehicles show significant spatial structure, neighbors within a certain radius are influenced most (Rai & Henry, 2016), the small-world network is a great way to represent that. To construct a small-world network the Watts-Strogatz model (1998) is used, this model addressed two weaknesses present in the Erdős–Rényi model; preventing triadic closure, and a higher clustering coefficient (Watts & Strogatz, 1998).

Given the desired number of nodes N, their mean degree K, and parameter β, the Watts-Strogatz algorithm constructs an undirected graph with N nodes and $\frac{NK}{2}$ edges. First, a ring lattice is constructed, then a set of edges (based on parameter β) is rewired to a random node to form non-lattice non-local edges. Subsequently, with these steps a locally clustered network is created. Since households are the nodes, the value of N is the same as the number of households in the model. The mean degree K is the number of connections per node, this is kept low as default with a value of 4. Individuals might have a social network with a large amount of people, but investment decisions have a tendency to be influenced by a smaller circle (Stavrakas et al., 2019). Ideally this parameter is based on survey data, unfortunately the section of the survey that covers social relations is designed to only consider 4 connections at most, so no correct node degree can be extracted from the survey data. The parameter β is the probability of rewiring an edge, a larger parameter β leads to more random non-local non-lattice edges, a lower average path length, a lower clustering coefficient, and fatter tails on the node degree distribution. The β parameter value is set at 0.1 in line with other literature (Maya Sopha et al., 2011) and shapes the structure and heterogenous number of social contacts households have.

Establishing an empirical foundation for social networks is difficult. A common issue is the lack of empirical data on how people spread information with each other (Delre et al., 2010). Solicitation methods are dependent on the network size (Maertens & Barrett, 2013) and connection data can be limited or costly (Rai & Robinson, 2015). As discussed earlier, the section of the survey that covers social relations is designed to only consider 4 connections at most, so no correct mean node degree for the social network can be extracted from the survey data. However, the survey data does include questions that consider age, income, education, and locational parity when it comes to communication of energy decisions (see table 8). It is clear from the data that the majority of people communicate energy decisions with others that have similar education (78.9%), age (70.7%), income (56.8%), and live nearby in a radius of less than one kilometer (51.3%). To reflect this in the model, the social network is modified to account for sociodemographic factors. Edges are assigned a weight based on the weighted sum of education, age and, and income similarity between the two households. This is done to achieve a more realistic reflection of reality, people with similar socio-economic status are more likely to have lifestyle affinity (Krause et al., 2007; Maya Sopha et al., 2011; Mollenhorst, 2015).

Table 8

Survey data for the question: "With whom do you usually, or would discuss with, or enquire information about, energy decisions and energy saving strategies? X in comparison to your X."

Characteristic	Response	Survey sample
Age (%)	Much younger	11.8%
	About my age	70.7%
	Much older	17.5%
Education (%)	Much lower	8.7%
	About the same	78.9%
	Much higher	12.4%
Income (%)	Much lower	13.6%
	About the same	56.8%
	Much higher	29.6%
Distance (%)	<1km	51.3%
	1km-5km	18.5%
	6km-10km	9.9%
	>10km	20.3%

The parity between households for the three sociodemographic factors is determined by equation 11, where P_x is the parity value between 0 and 1, v_{xa} is the value for that specific sociodemographic factor of node a, v_{xb} for node b, and R_x is the range for that factor.

$$P_x = 1 - \left(\frac{|v_{xa} - v_{xb}|}{R_x - 1}\right) \qquad (11)$$

Once the three parity values have been determined, these can be added in a weighted sum with weights based on the survey data.

$$w = w_{age} * P_{age} + w_{edu} * P_{edu} + w_{inc} * P_{inc} \qquad (12)$$

Ultimately, the edges of the social network are assigned weight w based on equation 12. When households determine the social utility—that represents the subjective norm TPB component—they do this based on their social network. If the majority of their social network has already adopted solar

PV, then the pressure to adopt is higher. This weight modifies the influence of the households on the social utility (see equation 4).

Geographical distance is not considered in the social network because no geospatial data was available for the survey. Instead, the geographical distance is emulated by the local connections and non-local connections (based on parameter β) from the Watts-Strogatz model, but not explicitly modelled despite 51.3% of the respondents usually discussing energy decisions with people closer than 1 kilometer.

Note that the social network and agent age are assumed to be static. While in reality our social network is dynamic and always evolving, the modelled social network is static; no relationships are formed or broken throughout the simulation.

5.5. Synthetic Population generation

Agent behaviour is largely dependent on agent attributes. The aim of the model is to realistically reflect social dynamics, therefore the agent attributes must reflect the real attributes of the households they represent (Chapuis et al., 2022). The agent attributes are especially important because some have shown to be significant indicators of the intention to adopt solar PV (see section 5.3.3). While attributes could be pulled from generic distributions, this does not guarantee that agents have realistic sets of attributes, take for instance a mismatch between a high-income class and a tiny house surface area. In this research population generation is achieved by generating a synthetic population based on the individual-level survey data. It is simplified in a sense because does not contain all real attributes, only major attributes such as age, income class and gender. Generating a synthetic population results in a synthetic population that is never identical to the target population, but it does approach the macro-level statistical measures (marginals) of the target population closely.

The goal is to minimize the difference in attributes between the generated population and the real population. This is achieved with the combinatorial optimization (CO) method which reproduces real entities from a sample of the population. Therefore, the two types of data required are: (1) macro-level data with distributions or aggregated values referred to as marginals, and (2) individual-level or microlevel data such as the data from a survey, from a portion of the whole population (Chapuis et al., 2022). An illustration that demonstrates the CO method is depicted below.

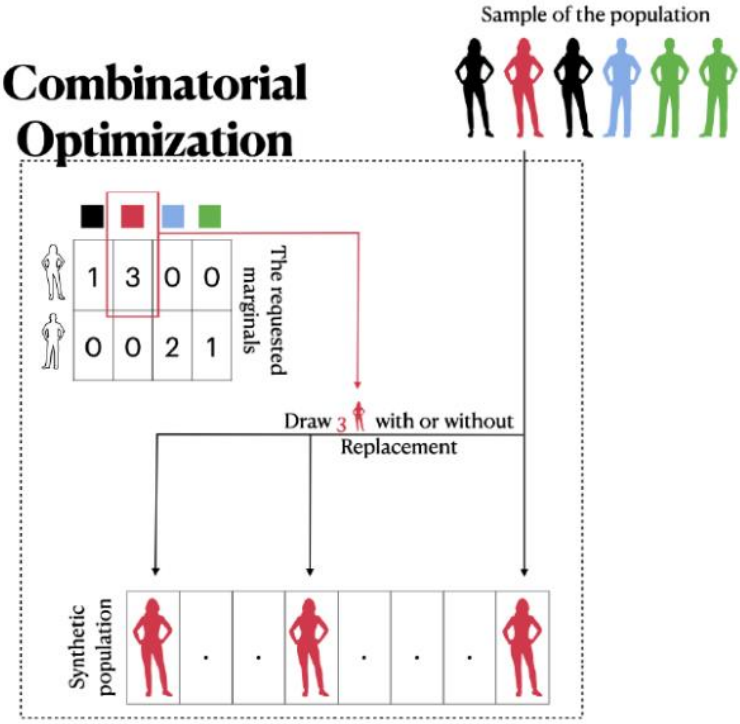


Figure 7
Combinatorial Optimization (CO) method, adapted from (Chapuis et al., 2022)*.*

The CO method draws individuals from a survey—in this case with replacement—to satisfy a fitness criterion (Chapuis et al., 2022). The process to minimize the difference in attributes between the generated and real population is as follows. The sample representing the synthetic population starts empty at first and is then filled with random individuals (and their corresponding microlevel data) from the survey data. The fitness criterion—chosen as the standard root mean square error (SRMSE) —can now be calculated (equation 13) to answer the question: How much do the synthetic sample marginals differ from the desired macrolevel marginals? Subsequently one individual is replaced with another random individual, if it decreased the SRMSE the synthetic sample got improved and is now closer to the real population, therefore the replacement is kept. If the SRMSE increased, the replacement is discarded. This is a simple hill-climbing algorithm that can be repeated until the SRMSE is within the desired error range or a set number of loops has been completed (see figure 8). The hill-climbing algorithm does not necessarily find the global optimum, instead it can reach a local optimum and get 'stuck'. The final synthetic population consists of reproductions (copies) of individuals from the individual-level survey data, but the population now also fits the desired marginals to accurately represent the real population. The fitness-based optimization algorithm is simplified to only consider aggregated average data for the population of The Netherlands.

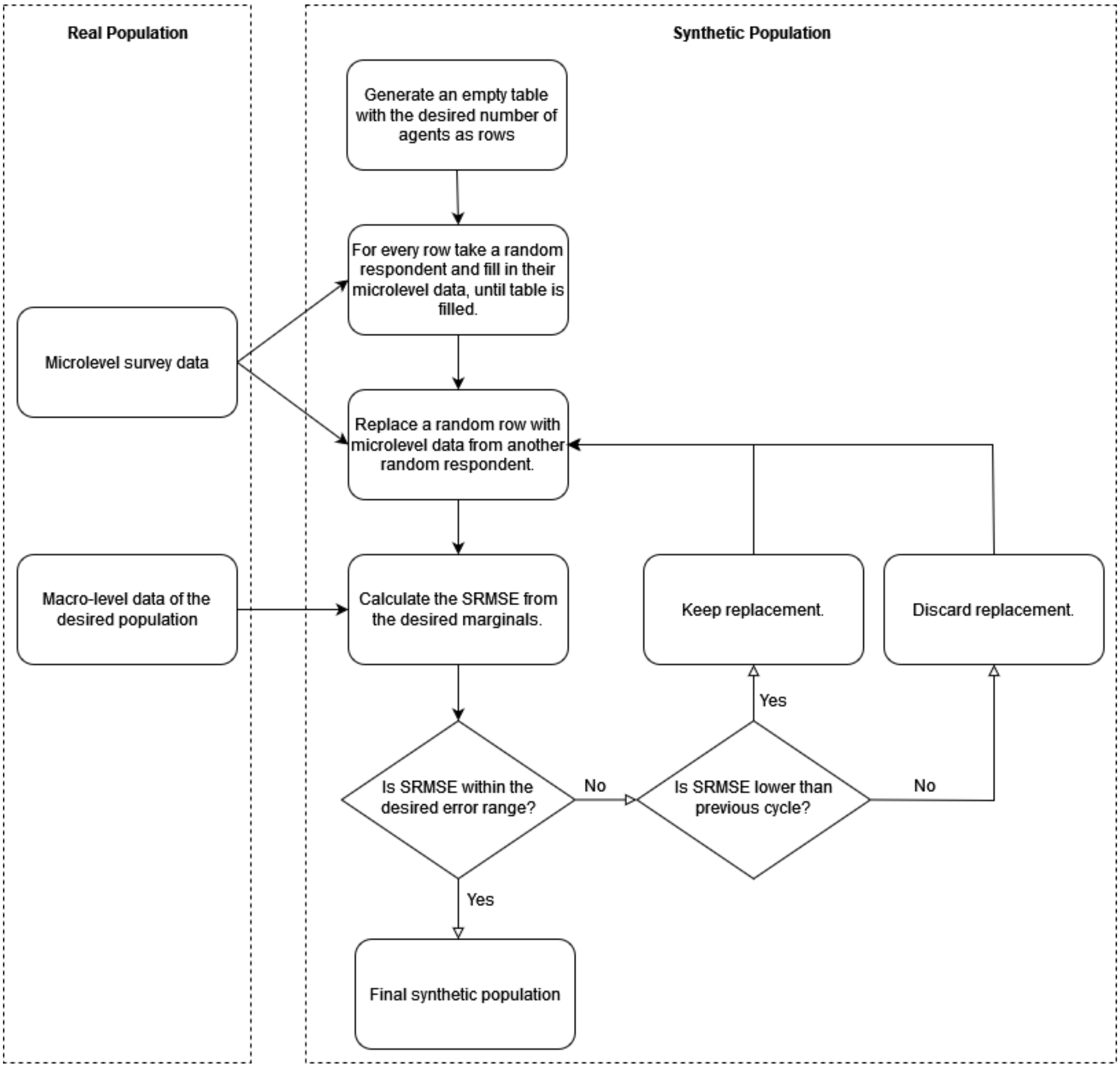


Figure 8
Flowchart of the synthetic population generation process.

The fitness criterion can range from basic total absolute error (TAE) or proportion of good predictions (PGP) to more complex fitness criterion such as relative sum of squared Z-scores (RSSZ). Combinations can be used, but in most cases a single aggregated fitness criterion fulfills the requirements (Chapuis et al., 2022). The standard root mean square error (SRMSE) is the most commonly used indicator (Chapuis et al., 2022) and will be used for this research (equation 13). Here X represents the set of all possible vectors, x represents a vector of attribute values, P_x and E_x are the predicted proportion of real households with vector x, and the actual distribution, respectively. A larger value indicates a larger discrepancy between the marginals of the current synthetic population sample and real target population.

$$SRMSE = \frac{\sqrt{\sum_x^X (P_x - E_x)^2}}{\sum_x^X P_x} \qquad (13)$$

The benefits of CO are multiple. National census data is used, but not to disaggregate into individual agents, instead the agents aggregate towards the census data. It ensures the single-user survey data gathered in Dalfsen, Overijssel is representative for all Dutch households. Additionally, CO ensures joint distributions are respected and the privacy of respondents is guaranteed due to the sampling procedure.

5.6. Supply side dynamics

Since the focus of this research is on the consumer behaviour, the supply side is modelled exogenously. The two most relevant exogenous variables are electricity price per kilowatt hour, and the CO2-emission factor of energy production in the Netherlands. Both are publicly available and are being actively monitored by CBS (CBS, 2020b, 2022a). Both the electricity price and CO2-emission factor are static, and data from 2020 is used to disregard fluctuations caused by the recent Ukraine invasion. The electricity price is used in the payback period calculations for solar PV, and the CO2-emission factor is used for the environmental utility component. Additionally, infrastructure such as the transport and distribution of electricity is demarcated, but the network costs are still factored into the electricity price the households pay.

To a lesser extent the CO2 savings per kWh is used for calculating the environmental utility factor and is assumed to be equal to the CO2-emission factor (CBS, 2020b). This is likely an underestimation because transportation losses from centralized generation are also prevented by decentralized solar PV electricity generation. Additionally, this value has seen a sharp decrease due to the increased rate at which fossil fuels are being replaced with renewable energy in the Dutch energy mix.

Taking a static electricity price is not quite accurate, as it ignores seasonal fluctuations and geopolitical impacts. However, the timesteps in the model are fairly large (at 1 year per timestep) so these fluctuations are less impactful. In experiment E6 scenarios with high electricity prices—that are currently at this level due to the energy crisis—are explored.

5.7. Assumptions

The previous sections already discussed assumptions that are made and their implications. However, not all assumptions that have been made during the conceptualization process were discussed in full. To understand the context of the model it is important to be aware of all the assumptions. Therefore, a full list of model parameters, their source, and assumptions can be found in Appendix D.

5.8. Conclusion

The model consists of various components that interact with one another. The conceptualization of these components has been discussed in this chapter. The agents represent Dutch households that may take actions, adopting or not adopting solar PV technology. They decide these actions based on the TPB utility factors that are altered by weights from the survey data. The social network of the households influences their subjective norms and thus their behaviour. The supply side is exogenously modelled since the focus is on the demand side household behaviour. These components are sufficient to establish a base case scenario that may be used to compare the effectiveness of various policy interventions.

6 Model Formalization & Implementation

In this chapter the model formalization and software implementation are presented based on the detailed model design discussed in the previous chapters. The aim of this chapter is to establish a model narrative, a story of how agents interact and how that gives rise to the emergent pattern, the attitude-behaviour gap. Model flow is discussed, and the implications of pseudorandom number generators are considered with reproducibility in mind. The modelling environment is discussed and justified, the model architecture is presented, and the choices for the model timestep and time horizon are discussed. Agent parametrization and agent heterogeneity are considered, as well as policy interventions and KPIs. Lastly, the model verification process is explained.

The sub question that is addressed in this chapter is:

SQ3: How can these factors be represented in an agent-based model?

6.1. Model Flow

The simulation flowchart (figure 9) presents a high-level overview of the model flow for a single run. This simulation flowchart is similar to the majority of ABMs. After initialization, within each timestep the model loops over the households and they perform their desired actions. After all the agents have performed their actions, the next timestep begins. While in reality the actions would be taken simultaneously, here the discrete timesteps mean the agents' behaviour is sequential. This is taken into consideration for the model narrative to ensure reproducibility. To prevent first-mover advantage the agent sequence is often randomized by default (Van Dam et al., 2013). For reproducibility the order of this sequence is made deterministic by setting the *random-seed* value (the seed of the pseudo-random number generator) in NetLogo, resulting in an identical sequence of households when they are called upon by functions that act on agent sets, if the same seed is chosen. This prevents situations where certain model runs cannot be reproduced because the order in which the agents act is not the same, for instance by influencing the social network and thus influencing the decisions of other agents in a different order. The downside of deterministic iteration of agents is the introduction of the first-mover advantage.

The model contains stochastic processes so a single run cannot be trusted, the run must be repeated multiple times to determine if the model results are representative and not outliers (Van Dam et al., 2013). The number of repetitions is set at 100 repetitions per run to err on the side of caution, and the reported results are the mean of these replications, with the standard deviation notated in parenthesis. The number of repetitions is identical for every run, no reductions are made for certain experiments in the parameter space.

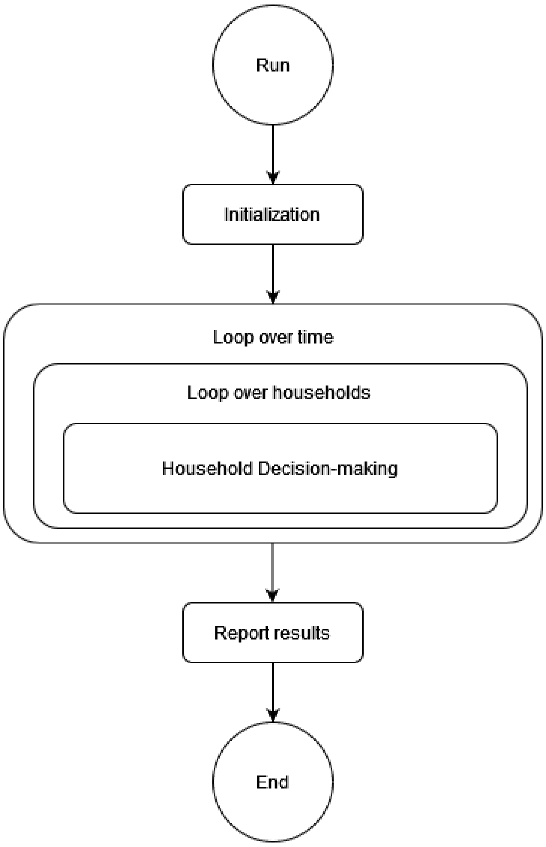


Figure 9
Simulation flowchart of the ABM

A more in-depth depiction of the model flow is shown in figure 10. The model flow diagram also acts as a model narrative in flow chart format. The model narrative in long sentence format is as follows: Firstly, the households that have not yet adopted solar PV attempt a probabilistic PBC check based on their income. If the PBC barrier is passed, the utility is calculated based on the information from the social network, personal attributes, and other environmental variables. With this information, the households can choose between two actions, to adopt or not to adopt solar PV, this choice is based on the multi-attribute utility functions. After a certain amount of time has passed, the suboptimal diffusion of cost-effective solar PV throughout the population leads to emergence of the attitude-behaviour gap.

Not all agent and global functions are executed every timestep, some functions are culled to reduce computational overhead. For instance, agents will not determine their multi-attribute utility functions unless the PBC barrier is passed, or even attempt the PBC barrier if they have already adopted solar PV. Likewise, social network dynamics are only determined when the social utility is requested.

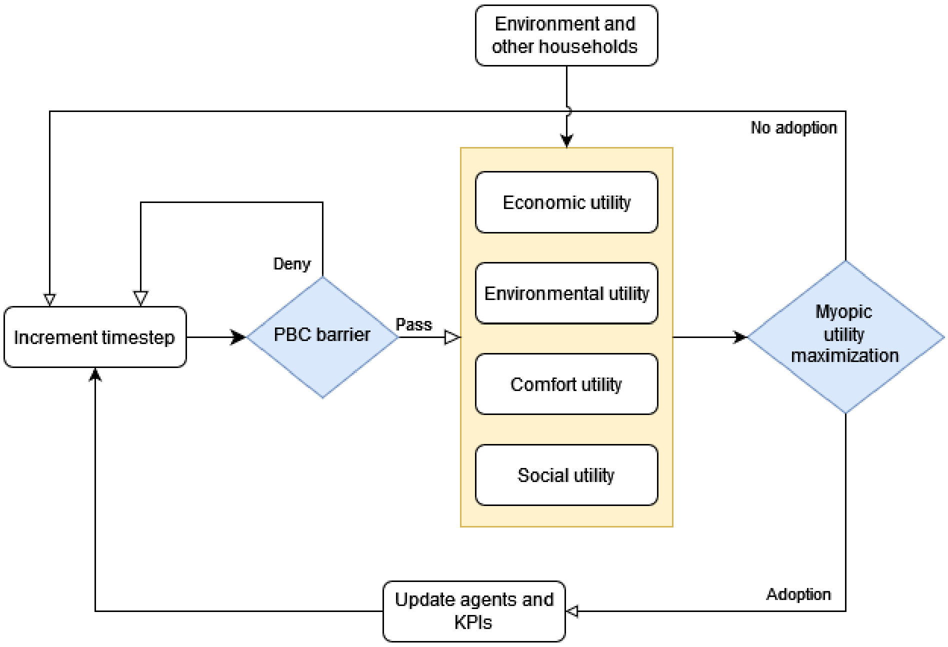


Figure 10
Model flow diagram of the ABM

6.2. Modeling Environment

The modelling software used to implement the model is NetLogo. It is a free, open-source software platform for creating ABMs that is widely used in academics (Wilensky, 1999). The modelling language is agent-oriented and part of a loose family of Logo languages, with some subtle differences. The NetLogo modelling environment offers a multi-agent environment, where interactions may happen between agents themselves, but also between agents and the environment. NetLogo also provides a set of predefined functions that aid the modelling process.

The advantages of NetLogo are: (1) it is well established due to the age, (2) There is thorough documentation, and a library of example models due to the extensive userbase, (3) it is created for academic purposes with emphasis on reproducibility, (4) it features tools for experimentation. The software platform NetLogo is chosen above the Python MESA library because of the advantages listed above. The downside of NetLogo is the data analysis and visualization are lacking compared to MESA. For reasons of MESA being a python library, it can more easily be integrated with other Python libraries such as Pandas, making it very convenient to analyze results and visualize data.

Netlogo does not include a feature for conducting global sensitivity analysis. Therefore, this was conducted with a Python approach. The Pynetlogo library (Jaxa-Rozen & Kwakkel, 2018) is used to link Python and NetLogo. The global sensitivity analysis is conducted with the sensitivity analysis library (SALib) library for Python (Iwanaga et al., 2022).

6.3. Model Time

The time horizon of the computational experiments should be long enough to observe the emergent pattern (Van Dam et al., 2013). A long time horizon of 40 years is chosen to ensure the emergent behaviour can be observed, even in experiments with initial conditions that may delay the emergence, because the lifetime of the technology is long and diffusion is a slow process. Preliminary analysis with initial runs (experiment E0) have shown that 40 years is sufficient in seeing the saturation of solar PV installation regardless of parametrization and policy interventions.

The model time is divided into discrete timesteps. The timesteps represent a period of 1 year, because

6.4. Parametrization

The process of choosing values for the parameters present in the model is situationally dependent. The values of the parameters come from various sources. From most to least preferred the sources are survey data, recent CBS data, similar literature, based on assumption, or the modellers' informed decision.

The parametrization of the model is performed at initialization, a chosen number of households are parametrized with attributes from the survey data, as described in sections 5.3 & 5.5. The location of these households is randomized, geographical distance does not play a role in the social network. The social network is initialized with two key parameters that influence network degree and average path length. Parameters representing technical aspects of the solar PV installations are based on CBS data. For an extensive list of model variables, their parametrization and data sources refer to Appendix D.

Policy interventions also come with parameters that are adjusted per run, for instance the amount of a subsidy or tax. To determine the impact of certain initial parameters on the model outcomes a sensitivity analysis is performed, these results can be found alongside the results of the experiments in chapter 7.

6.4.1. Agent Heterogeneity

Agents are heterogenous in their personal attributes (income class, age, gender, attitudes), dwelling characteristics (house size, house type, house age) and in their preferences for solar PV, based on the weights resulting from the statistical analysis of the survey data. The agents are initialized with a simplified combinatorial optimization algorithm (see section 5.5), which leads to heterogenous synthetic populations. Even the synthetic populations themselves may differ (if the random-seed is not set) because the algorithm is random. The social network is also a source of heterogeneity, some agents have a higher degree than others and thus a larger social network with more social connections, their decisions influencing a larger group of households.

6.5. Policy Intervention Implementation

To address sub question 5 and 6 policy interventions must be implemented. The model lends itself well to a variety of policy interventions, the implemented policy interventions are the Dutch salderingsregeling, tax rebates, soft loans, information campaigns and technology seeding. The goal is to investigate what policy interventions can contribute towards closing the attitude-behaviour gap and what their effectiveness is. Policy interventions target the barriers to adoption of households, thus increasing the diffusion rate by reducing reasons against adoption, allowing positive attitudes to control the decision-making. Public policy support is shown to be a key factor for increasing the diffusion of solar PV in countries like Germany, Denmark, and Spain (Claudy et al., 2013). The literature review demonstrated that the spotlight is often on financial instruments, and on the introduction of new policies, rather than phasing out or discontinuing existent policies. The exact parametrization of the policy interventions may be found in Appendix D.2.

6.5.1. Salderingsregeling

Feed-in tariffs are claimed to be successful in stimulating the adoption of solar PV (Claudy et al., 2013). They have been widely introduced and are considered the most efficient and effective instrument to promote diffusion (European Comission, 2012).

The Dutch salderingsregeling is an already existent feed-in tariff aimed at small-scale users to stimulate adoption of solar PV technology by making it more economically attractive for adopters. An in-depth explanation is offered in section 4.4, and figure 11 illustrates the phase-out. This is a very relevant topic considering the current discussion around the topic, to consider what the potential effects of phasing out the *salderingsregeling* are on the adoption of solar PV installations. Three scenarios are considered, one business-as-usual scenario where the *salderingsregeling* is continued, a scenario where the *salderingsregeling* is phased out completely, and a third scenario where the *salderingsregeling* is phased out but an 80% return fee[3] remains in place. The exact values for the proposed phase-out are shown in table 1. In the model this financial instrument affects the discounted cash flow calculations that determines the revenue of the solar PV installations for households.

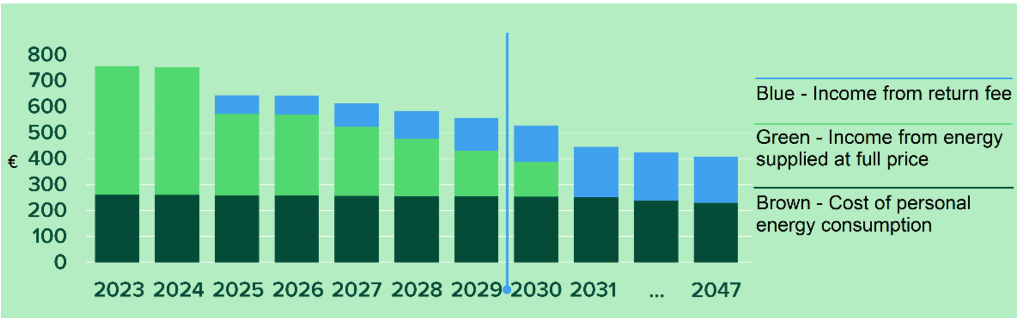


Figure 11
Visualization of the proposed phase-out of the salderingsregeling. Brown indicates the constant personal energy consumption cost, green is the income from energy that may be supplied at full price, blue indicates the income from energy supplied for a return fee. The blue line indicates the time at which the investment cost has been recovered, roughly 7 years. Adapted from (Milieu Centraal, 2021).

[3] 80% of the consumers' contractual electricity price. The return fee is given for the fraction of electricity that is 'overproduced', when a household generates more electricity than they consume.

6.5.2. Tax rebates

Tax rebates are a financial instrument that allows households that adopt solar PV to deduct a certain percentage of the purchase cost, or a certain amount per unit of energy consumed, from their taxes. Rebates stemming from public funds have raised equity concerns (Rai & Robinson, 2015) because solar PV adopters are wealthier than average (Rai & McAndrews, 2012). Rebate programs that are designed to decline over time are more cost effective (van Benthem et al., 2008), likely due to social dynamics and subjective norms.

Currently, households and small businesses in The Netherlands have the right to a one-time tax rebate when investing in solar PV installations for the first time (Rijksoverheid, 2022). This tax rebate is equal to the BTW-value of 21% of the total installation price, and drastically reduces the payback period of solar PV installations in The Netherlands. This intervention targets the high upfront cost barrier normally associated with solar PV installations. Three scenarios are considered, the current 21% tax rebate, a 10% tax rebate, and no tax rebates. Tax rebates are implemented as a factor (or a flat fee) that adjusts the total cost of a solar PV installation.

6.6. Key Performance Indicators

The key performance indicators (KPIs) are the output variables of the model that are recorded at every time step. The four most relevant KPIs are (1) the rate of diffusion, (2) the annual solar PV energy production, (3) the annual CO2-emissions prevented, and (4) the total costs saved.

The most important KPI is the rate of diffusion, synonymous with the rate of adoption, market share, or market penetration. This KPI is determined every timestep by determining the households with solar PV installation divided by the total amount of households, this is presented as a fraction. This KPI indicates the emergence and magnitude of the attitude-behaviour gap, determined by comparing it to the 'true social optimum'.

The annual solar PV energy production is measured as GWh/year and represents the total annual electricity production of all the solar PV installations combined. This value increases as more households adopt solar PV.

The annual prevented CO2-emissions, as the name suggests, is based on the CO2-emissions that would be prevented by households consuming electricity from their solar PV installations instead of electricity from the electricity providers, based on the CO2-emission factor of energy production in the Netherlands (CBS, 2020b). Measured in ktonne/year.

The payback period for solar PV installations is generally less than the lifetime of the installation, leading to cost savings when compared to households buying electricity from the electricity providers. This KPI is measured in M€.

Other outputs are also tracked, such as the distribution of income classes of PV adopters, the fraction of low-income adopters, and cumulative number of PV systems installed. These outputs are used in determining the effectiveness of policy interventions or to support conclusions. Similarly, the model variables such as tick, random seed, and attributes of agents are recorded.

6.7. Model Verification

Model verification is performed to determine whether the conceptual model is implemented correctly. The agents and their relationships are analyzed and compared to the conceptual model to check if the model is built right (Van Dam et al., 2013). Verification often is a difficult task for agent-based models due to the complexity introduced by the large number of agents, their states and their actions (Van Dam et al., 2013). Especially so considering the exploratory nature of this research, since the emergence of the attitude-behaviour gap is still underexplored. Three of the four techniques suggested by Van Dam et al. (2013) are applied in the verification process; tracking agent behaviour, single-agent testing, and interaction testing in a minimal model. These three methods are discussed in further detail in the following subsections.

6.7.1. Tracking Agent Behaviour

To ensure the agents are operating as expected their behaviour will be tracked and analyzed. This is performed in different approaches: (1) record the inputs, states, and outputs of agents, (2) log the inputs, states, and outputs for internal processes, and (3) run through the code with a debugger (Van Dam et al., 2013). These approaches are discussed in further detail in the following paragraphs.

The model already includes several KPIs that are used to record the output of the model, with these KPIs the emergent behaviour can be tracked as well. In one of the first iterations of the model the KPIs were deliberately implemented to analyze the system effects of certain parameters and processes while coding. This aided in finding major flaws when new components of the model were added, as they were clearly visible in the outputs of the model.

The behaviour of agents can be tested by inspecting their states before, during, and after a model run. By watching the agent state during a model run one can gain insight into the internal 'thought' process of the agent (Van Dam et al., 2013). The decision-making of agents is straightforward in a sense that it is only one decision-making process, however, it is a complex process dependent on many different aspects. Therefore, this step was crucial and was performed numerous times throughout the modelling process. The NetLogo inspect feature is the perfect tool for inspecting the agent states at a certain timestep, but not suited for analyzing the evolution of the states. For this purpose a .csv file was written for a set of runs, with the internal agent states for every timestep. By analyzing this .csv file undesired fluctuations in variables—or other errors that may occur between initialization and stop—could be identified and solved. The time horizon of the model is not very long so the series of states is not difficult or time consuming to inspect, instead the issue is the number of agents and choosing the correct one to inspect.

In the NetLogo software environment is interactive. NetLogo features a mandatory debugger, it is mandatory in a sense that the model cannot be run if there are syntax errors. Unfortunately, break points cannot be set in the NetLogo environment. A way around this is a large amount of print statements in methods of the code that detail what is happening under the hood. In figure 12 an example of these print statements used to verify the CO initialization and social network can be seen, they include practical information such as network metrics or other values. Similarly to print statements, plots are also used to debug agent attributes or the social network (see figure 13). Additionally, the profiler extension was used to see how frequently methods are called, and what methods are time consuming, in order to identify sections of code that should be optimized.

```
SRMSE: 0  SRMSE_delta: 3.49274100469759E-5  cycle: 42095
FINAL SAMPLE -- SRMSE 8.002875018469571E-4  SRMSE_delta 3.49274100469759E-5
NETWORK METRICS -- Mean Node degree: 4  Clustering coefficient: 0.341  Mean Path length: 8.491  Link count: 2000
```

Figure 12

Print statement of the CO hill-climbing algorithm and social network metrics for verification purposes.

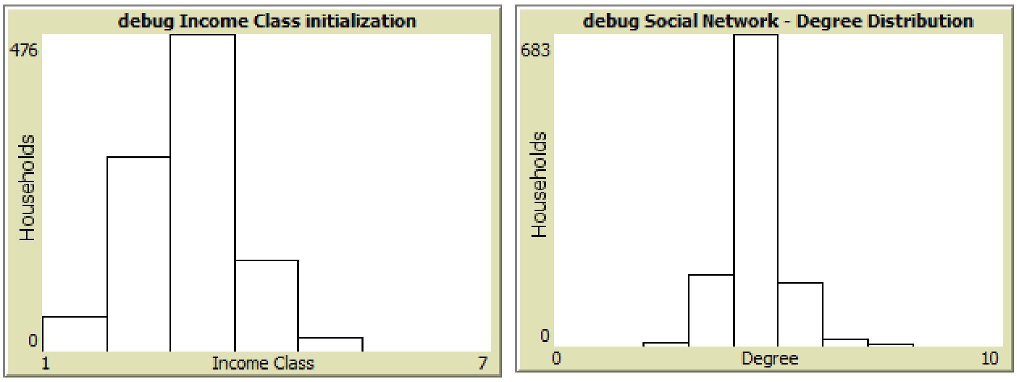


Figure 13

NetLogo debug histogram plots for agent income class and node degree distribution for verification purposes.

6.7.2. Single-agent Testing

Instead of looking at the big picture, a more focused verification method may yield different results. The model consists of many agents, network connections, and interactions that are interrelated and influence one another. Therefore, it may sometimes be difficult to determine where unexpected behaviour comes from. This verification method addresses that issue by only considering a single agent.

Theoretical predictions were performed to test the model narrative. In such a scenario the model inputs are defined and there is a clear expectation of what an agent should do. For instance, a run where the initial adoption rate of solar PV in the population is 99.9%, only one agent has not adopted solar PV yet. Leading to an extremely high subjective norm through the social network, resulting in a high pressure on the household that has not yet adopted solar PV to do so. In such a scenario, the household acts as expected and adopts solar PV themselves as well. This test was done to verify the decision-making process of the agent, if it had not adopted solar PV it would point to an error.

6.7.3. Interaction Testing in a Minimal Model

Similar to single-agent testing, this verification method is performed with a limited number of agents. The absolute minimal model is considered, in this case four agents and a very limited social network (figure 14). The interactions between agents happens as intended, but the emergent effect is extremely dependent on the initial share of solar PV installations and always happens in the first timestep instead of gradually.

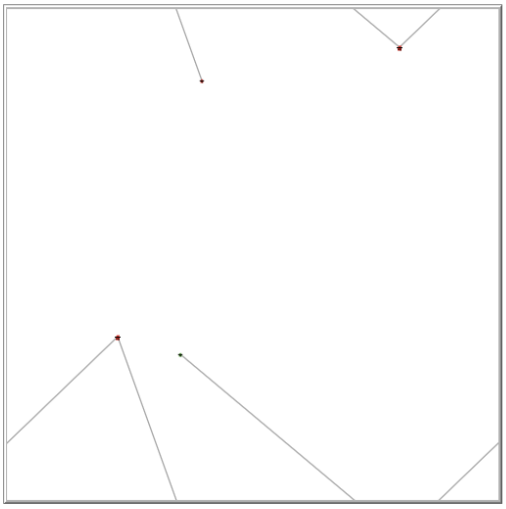


Figure 14
The interaction test in a minimal model with 4 agents. Note that while it may not look like it because the world is a torus shape that 'wraps' around, the households are connected in a social network. The household sprites are extremely small due to being scaled with node degree that is very low in this example.

6.8. Conclusion

The model formalization and implementation were described in this chapter. The choices made for the time horizon and time steps were justified. The parametrization for both agents and policy interventions was discussed. The KPIs that track the model outputs were presented, and lastly the verification was performed using three verification techniques from van Dam et al. (2013).

7 Model Results

In this chapter the results of the experiments are presented, and interesting results are highlighted and discussed in the text. Subchapters are indexed by experiment number as seen in the experimental design table (table 2). Firstly, psychological factors that contribute towards the emergence of the attitude-behaviour gap in Dutch households are analyzed in experiment 1. Secondly, two base cases are established. Base case B (E3) represents the current Dutch policy situation; therefore, this is the scenario that many experiments are compared against. Thirdly, policy interventions are explored to see if they can contribute towards closing the attitude-behaviour gap. Subsequently, scenarios with high energy price and scenarios to explore social effects and the effects of PBC are considered. Lastly, a sensitivity analysis is performed and presented.

Experiments are compared by the four main KPIs: diffusion rate (as fraction), annual energy produced by solar PV installations, annual CO2 emissions prevented by not consuming electricity from the grid, and lastly the cumulative costs saved by the households due to generating their own electricity. Specific experiments may be analyzed by comparing additional recorded outputs, such as PV adopter income class distribution.

Model results are parsed from .csv file and presented in plots generated by the Python Seaborn library (Waskom, 2021). In each figure 100 repetitions are plotted, in addition to the mean of these repetitions. The full table with results may be found in appendix E. Since the development over time is an important aspect of the diffusion rate, results are plotted with time on the x-axis. Year 0 represent timestep 0, or the year 2022. In the experiments, the initial percentage of households that already installed solar PV is 20% of the total population. Therefore, most graphs illustrate this at timestep 0 as starting point for the diffusion process.

In the model, every household can adopt solar PV. Under most circumstances, the choice to adopt solar PV is economically beneficial for every Dutch household. If solar PV were to reach their full potential, the 'true social optimum', every household in the model would have adopted solar PV at the end of the simulation. However, in almost all simulation experiments the diffusion of the energy-efficient technology does not reach the full potential, meaning that households do not engage in behaviour that would be justified, even if there are personal financial net benefits. Therefore, the attitude-behaviour gap is considered to be the gap between optimal diffusion (100%) and the recorded diffusion rate at the end of the simulation experiment.

The sub questions addressed in this chapter are:

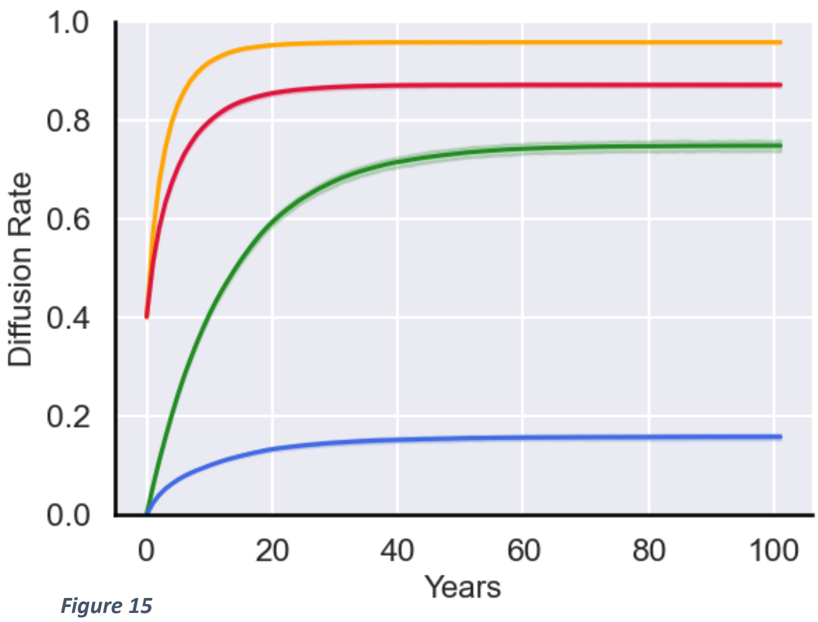
SQ4: To what extent does each identified factor contribute towards shaping the attitude-behaviour gap?

SQ5: What are policy interventions that can contribute towards closing the attitude-behaviour gap, and what is their effectiveness?

7.1. Preliminary Investigation (E0)

The purpose of the preliminary investigation is to explore the model behaviour and to determine a time horizon for the remaining experiments. In this experiment (E0) the diffusion process and the emergence of the attitude-behaviour gap are investigated. A very broad time horizon is used to see whether and when the diffusion process generally converges, at what timestep, and with what input parameters. This preliminary analysis of the parameter space allows a time horizon to be determined for the remaining experiments. Input parameters are subjectively set to unrealistic extreme values to observe the impact on the diffusion process in these edge-case scenarios.

A time horizon of 100 years is chosen for this experiment to ensure the emergent behaviour can be observed, even in experiments with initial conditions that may delay the emergence, because the lifetime of the technology is long, and diffusion is a slow process.



Line	Initial adoption percentage	Benefits of adoption
Orange	40%	High
Red	40%	Low
Green	0%	High
Blue	0%	Low

Figure 15

Results of the preliminary investigation with a long time horizon (100 years) and unrealistic input parameters. The orange and red lines start with an initial adoption percentage of 40%, while green and blue start with 0%. Parameters are more favorable for adoption for orange and green in comparison to their counterparts.

Due to the input parameters some scenarios converge earlier than others. When input parameters are favorable for solar PV adoption the diffusion process tends to converge earlier, as illustrated by the red and orange line in figure 15. When the input parameters are not favorable towards adoption the diffusion process starts slower, and converges later, as indicated by the green line that converges at roughly 60 years. Ideally the time horizon would be set at 60 years based on these results, however computational overhead must also be taken into consideration. There is a trade-off between computation time and satisfying edge-case scenarios with unrealistic parameters that will not appear in the experiments.

In all scenarios with realistic input parameters convergence occurs before year 40, therefore 40 years is chosen as the time horizon for all experiments. This preliminary analysis has shown that 40 years is sufficient in seeing the saturation of solar PV installation with realistic parameters, regardless of policy interventions.

7.2. Contribution Towards the Attitude-Behaviour Gap (E1)

With the empirically grounded ABM the decision-making of households can be studied, in order to understand what psychological factors may cause the attitude-behaviour gap of diverse Dutch households. Various psychological factors exist in the environment of the agent and influence their decision-making. Important psychological factors analyzed in this experiment are the perceived behavioural control of households, the importance of their initial beliefs, the influence of social learning, and the resistance towards solar PV investments due to economic uncertainty.

These input parameters are varied to study their contribution towards the output variable variance, the diffusion rate KPI. This illustrates the share in variance explained by each psychological factor, thus allowing us to see to what extent these factors contribute towards the emergence of the attitude-behaviour gap in Dutch households.

This is achieved by performing a time-dependent global sensitivity analysis (GSA). While generally sensitivity analysis is performed to demonstrate the robustness of conclusions under various assumptions (as it has been performed in section 7.7), sensitivity analysis may also be performed to show what model elements have the strongest influence on the results, and how interactions between model elements may influence model results (Borgonovo et al., 2022). The GSA is time-dependent in a sense that it is performed for every timestep of the model. This illustrates the dynamic nature of the psychological factors, and how their importance might change throughout the technology diffusion process.

7.2.1 Time-sensitive Global Sensitivity Analysis

This section considers the GSA methodology and tools required to perform it. The uncertainty in the outcomes is analyzed to see how strongly this uncertainty can be apportioned to the uncertainty in input parameters (Iwanaga et al., 2022). The output parameter is the most important key performance indicator, the diffusion rate of solar PV. The sensitivity of the inputs is represented by Sobol sensitivity indices, a higher index means the output is more strongly affected by changes in the input parameter (Sobol, 2001). Two different sensitivity indices are presented: the first-order index that measures the contribution to the output variance by a single input parameter, and the second-order index measures the contribution to the output variance caused by the interaction of two model inputs (Iwanaga et al., 2022).

NetLogo does not feature a built-in sensitivity analysis feature, therefore a Python approach is used. To connect NetLogo with Python, the Pynetlogo library for Python is used (Jaxa-Rozen & Kwakkel, 2018). Pynetlogo acts as a bridge that allows Python and NetLogo to communicate with one another. The analysis is conducted with the sensitivity analysis library (SALib) library for Python (Iwanaga et al., 2022). This library is used to generate an input parameter sample from the parameter space (table 9). More specifically, the Saltelli's extension of the Sobol sequence is used to generate a quasi-random low-discrepancy sequence of input parameter samples (Saltelli, 2002; Saltelli et al., 2010; Sobol, 2001). Six input parameters are tested with 512 runs, resulting in a sample size of 7168 (n(2p+2)). Unfortunately, this sample size is relatively small due to computation limitations and will result in larger confidence intervals for the Sobol indices than desired. The computational overhead was reduced with parallelization with the ipyparallel package (IPython Development Team, 2022), allowing the Netlogo model runs to utilize multiple CPU cores, but the time required for simulation runs was still significant nonetheless.

7.2.2. Input parameters

The set of six input parameters that are explored in the time-sensitive global sensitivity analysis are key parameters in the model that govern the behaviour of the households, as illustrated in figure 16. These parameters are psychological factors that play a role in the decision-making of households and these factors constitute the system level behaviour. The results are specific to Dutch households due to the survey data used for agent parametrization. Note that figure 16 only displays five input parameters, as the economic uncertainty is split into two parameters during operationalization, a mean component and a standard deviation component.

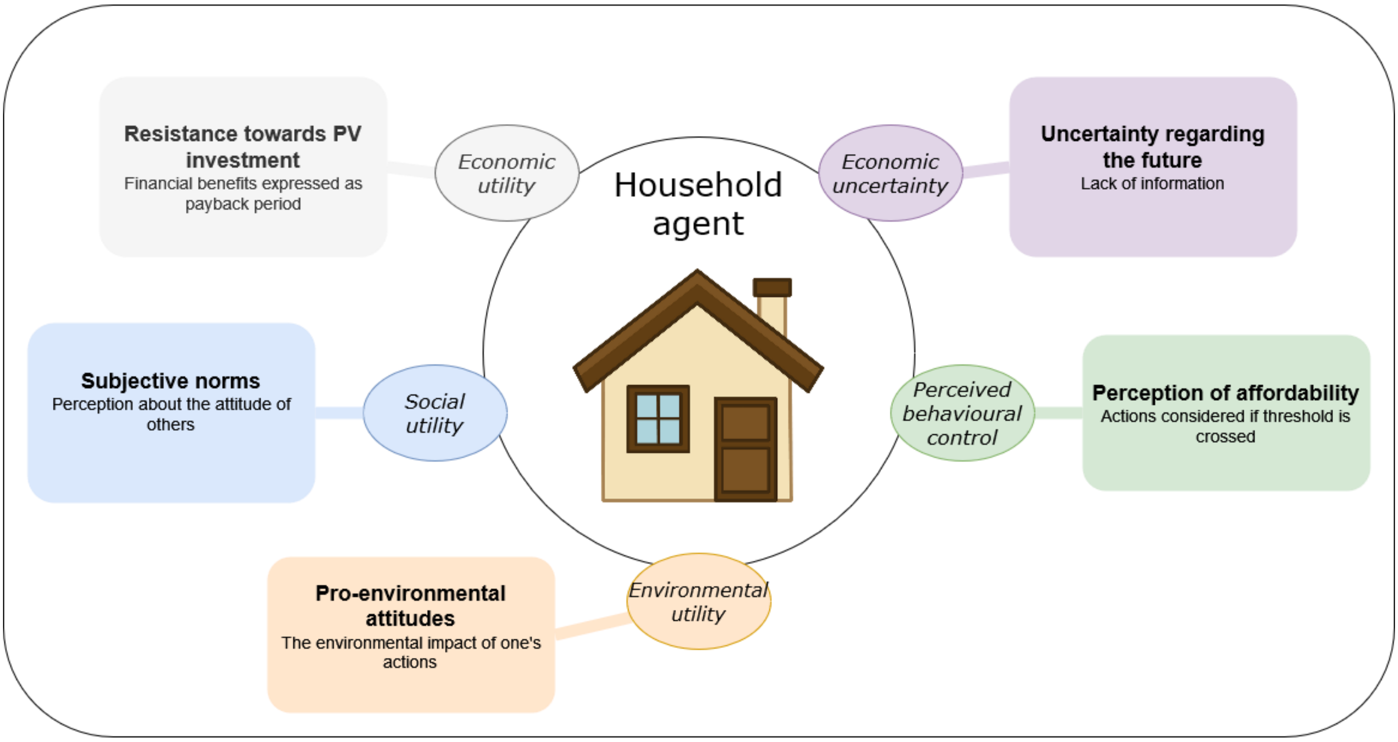


Figure 16

The set of household parameters adjusted in the time-sensitive global sensitivity analysis. Note that the economic uncertainty requires two parameters, increasing the total to six parameters.

Every household has a heterogenous set of initial beliefs expressed as weights, derived from the survey data. These initial beliefs represent the households' personal attitudes, knowledge, and biases towards the three context-dependent factors: economic, social, and environmental utility. These utility factors are seen on the left-hand side of figure 16.

Firstly, the probability of investing is represented by the economic utility, expressed as the payback period of investing in a solar PV installation. The financial benefits of investing in solar PV are considered by the households. Secondly, social utility stems from subjective norms; the perception about the attitude of others. This includes the perception of social expectations and social pressure exerted by comparisons to other households. This social pressure is altered by the 'trust' of households in each other, based on the age, income, and education parity between households. Thirdly, the environmental awareness of agents plays a role in the decision-making process of households. Households who possess pro-environmental attitudes care about the impact on the environment that their action creates.

On the right-hand side of figure 16 the PBC and economic uncertainty are shown. The perceived behavioural control (PBC) is the households' belief of the extent to which they can control their behaviour, similar to self-efficacy or locus of control. The perception of affordability is a significant barrier to adoption, therefore only the financial component is considered for the PBC. This is expressed as an income barrier constraint for households.

Economic uncertainty considers the lack of information of households and the uncertainty in electricity prices, this was added because the electricity price in the model is static. These aspects act as barriers to adoption for households when they consider the economic utility of solar PV. This uncertainty is expressed in a normal distribution that supports the households' decision to stick to the status quo, to not adopt solar PV. This is also the reason for only having five parameters displayed in figure 16, because the normal distribution takes a mean and standard deviation parameter it requires two parameters, increasing the total to six parameters.

Other parameters that are not considered in this list are set to their default values, identical to base case B (E3). In the presentation of the model outputs timestep 0 of the time-dependent GSA is omitted because in this timestep no model outputs are produced, it is only the initialization stage of the simulation model.

7.2.3. Experiment E1 Results

The results of the time-dependent global sensitivity analysis are found in figure 17 shown below. Throughout the simulation the most influential factor is the social utility, which is governed by the interactions between households in the small-world network. The second most influential factor is the mean of the economic uncertainty distribution (0.429 at timestep 40), while the standard deviation of this distribution is almost irrelevant.

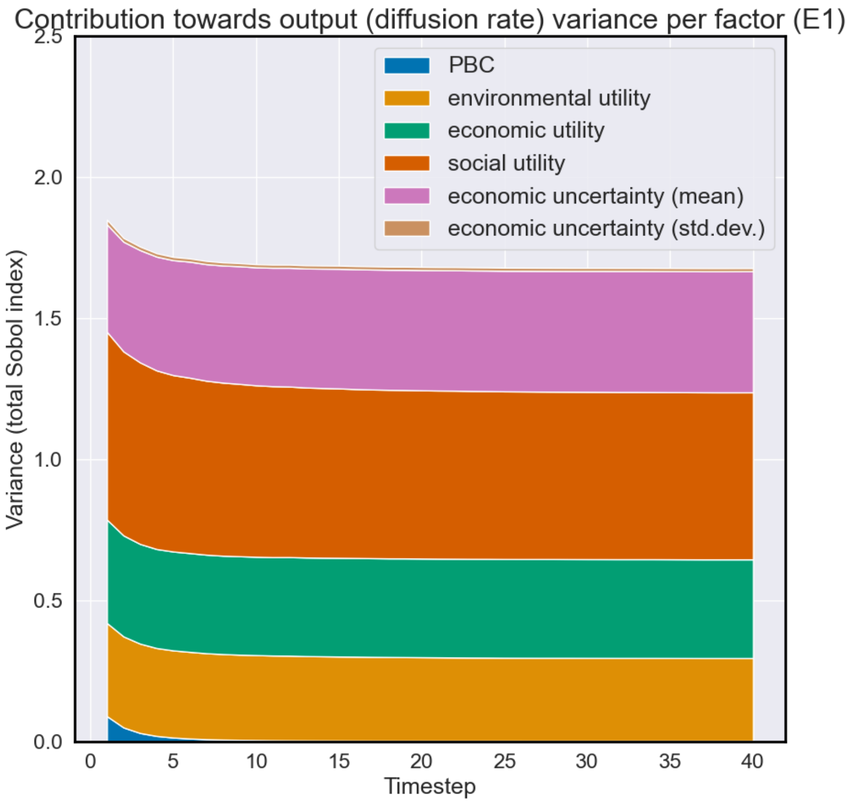


Figure 17
Share of variance in diffusion rate explained by each factor (7168 samples).

The evolution of the factors is not significant, except for the PBC factor, especially in the earlier timesteps before it converges after year 10. The factor that decreases most is the perceived behavioural control, contributing to the attitude-behaviour gap only in the first 10 years. Furthermore, the contribution of every factor decreases throughout the simulation, with the only exception being the economic uncertainty (mean), which increases from 0.380 to 0.429. Other factors such as the environmental utility, economic utility and economic uncertainty (std. dev.) don't evolve as much as the social utility and economic uncertainty do. Factors that do evolve, don't do so drastically and so the order of importance of the factors remains the same throughout the diffusion process.

In figure 18 a snapshot of the first timestep and last timestep are displayed as a bar graph to illustrate the evolution of the factors throughout the diffusion process. The first thing to note is the relatively large 95% confidence intervals due to the limited number of samples. Orange bars indicate the direct contribution towards the output variance, and blue bars indicate the first-order Sobol indices that reveal the contribution towards the output variance when accounting for interactions with other input parameters.

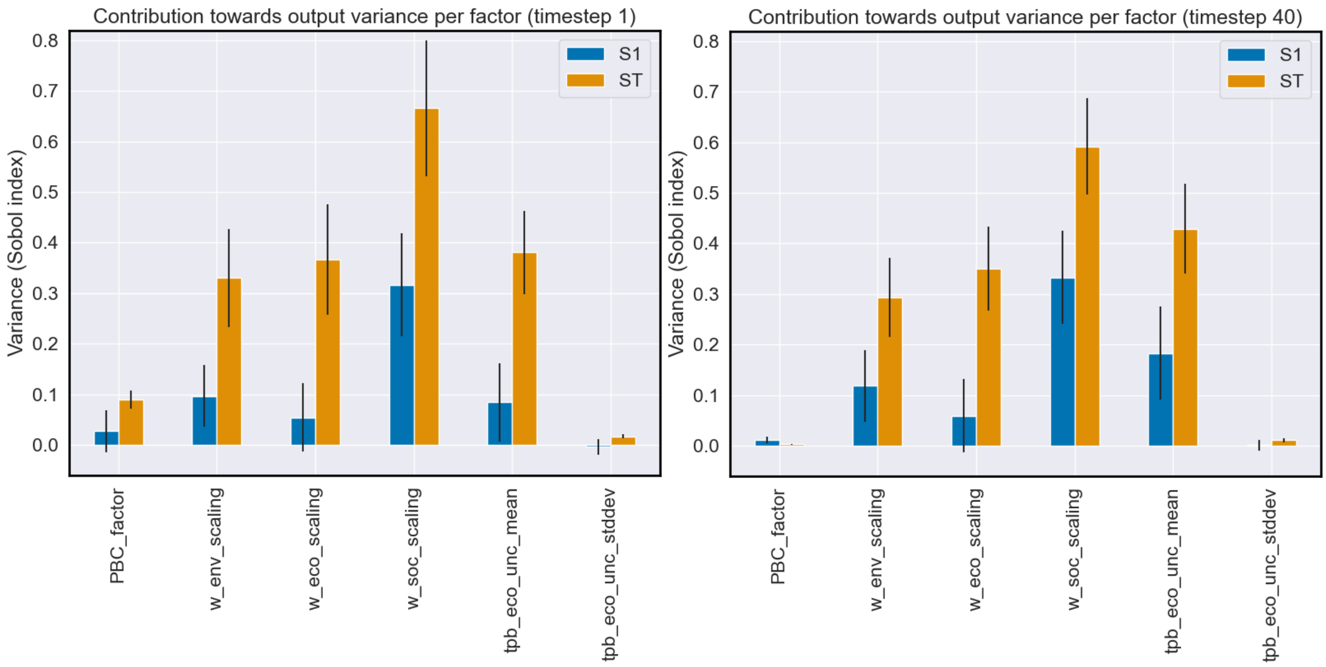


Figure 18
Total Sobol index (ST) and first-order interaction index (S1) at timestep 1 and timestep 40, with 95% confidence interval error bars.

In the model the social effects have a strong impact on the emergence of the attitude-behaviour gap. Households make social comparisons with other households in their social network, this leads to social pressure to stick to the status quo or to adopt solar PV. The social pressure of these two actions is shown in figure 19 shown below, here the status quo is displayed in red and the pressure to adopt is green. The crossover point occurs when roughly 50% of the population has adopted, it does not occur at exactly 50% due to weights (that represent trust) imposed on the connections of the social network. Notice the convergence of the social pressure curves occurs at the same time as the technology saturation, when no new households adopt solar PV anymore. In early stages of the simulation the social effects act as a barrier to adoption, the pressure to stick to the status quo is higher than the social pressure to adopt solar PV. While in later stages of the model the social pressure to adopt solar PV is greater than the pressure to stick to the status quo.

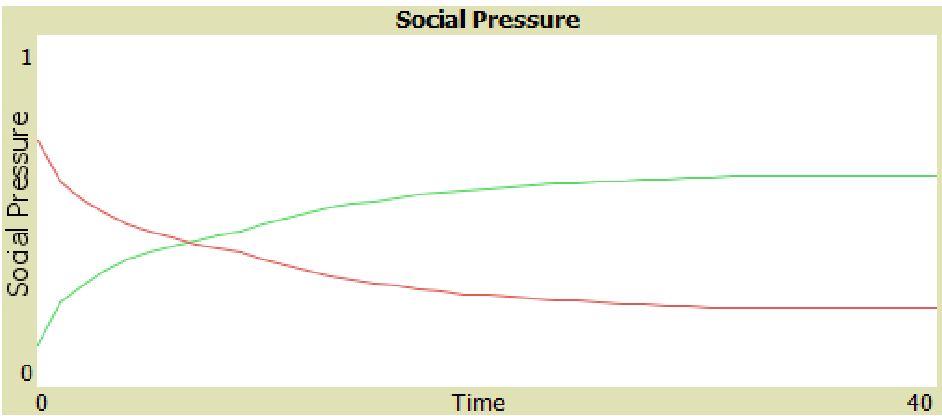


Figure 19
Social pressure for the actions of adoption (green) and not adopting solar PV (red) throughout the simulation.

7.2.4. PBC Operationalization

When the operationalization of the PBC component is set to act as a threshold income barrier instead of a probablistic income barrier, it plays a larger role in the variance of the diffusion rate. In the other experiments a probabilistic PBC income barrier must be passed by households before they consider solar PV adoption, causing low-income households to still have a slim chance of considering adopting solar PV. In contrast to a threshold PBC income barrier that leads low-income households to never consider adopting solar PV if their PBC is below the threshold PBC value. This results in a diffusion rate that is very sensitive to the PBC threshold value (figure 20) with a total Sobol index of 0.458, only slightly less than the social utility at 0.486.

Regardless of the PBC operationalization, the social effects remain a strong contributor towards the output variance of the diffusion rate.

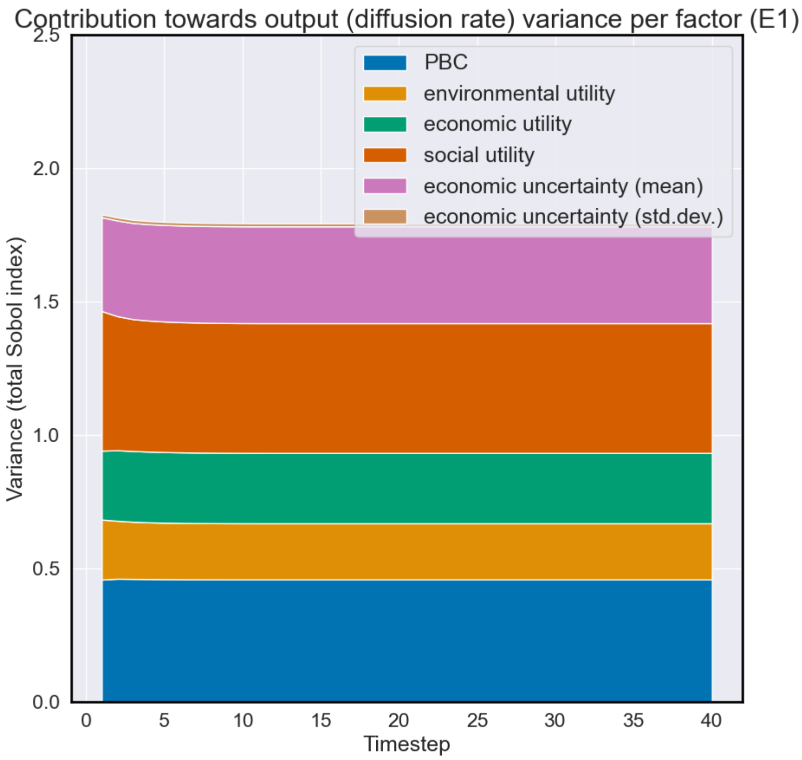


Figure 20

Share of variance in diffusion rate explained by each factor, with PBC operationalized as threshold.

7.3. Base Case Scenarios (E2 & E3)

The purpose of the base case scenarios is to act as scenarios that may be used to compare with other scenarios that have policy interventions, to determine the effectiveness of policy interventions. Two experiments that act as base case scenarios are run, one scenario with no policy interventions (E2) and another scenario with the current Dutch policy landscape (E3). Both scenarios feature realistic input parameters (appendix D), the only difference is in the tax rebates and *salderingsregeling* parameters, experiment E2 has both disabled and E3 has both enabled.

7.3.1. Base Case A (E2)

The results of the 100 repetitions for this scenario are displayed in figure 21. Base Case A portrays a scenario where there is no public policy support for residential solar PV. It results in two economic barriers to adoption limiting the diffusion rate, the high upfront costs and lack of capital of households. This is reflected in the poor diffusion rate, only reaching 27.7% of the total population, up from the initial percentage of 20%.

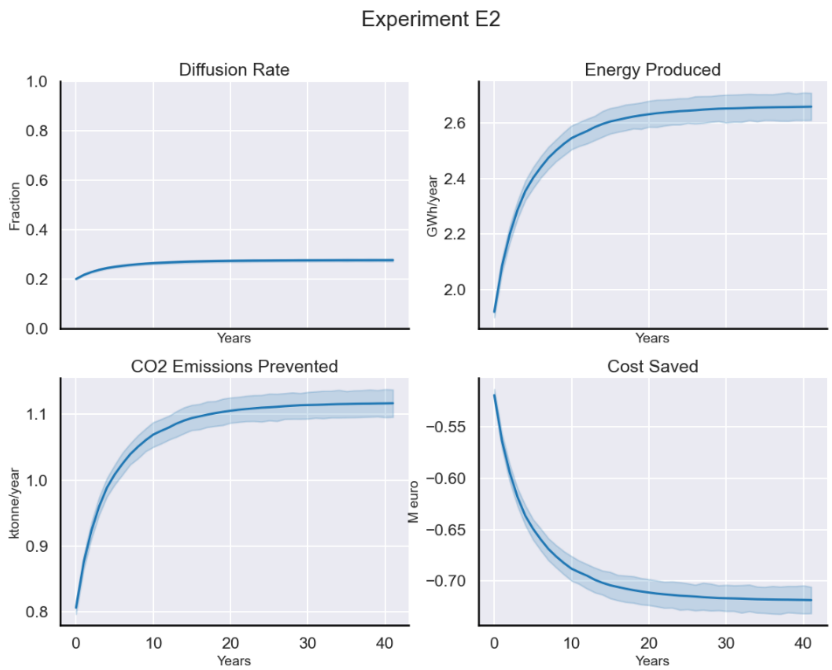


Figure 21
Key performance indicators for 100 repetitions of experiment E2.

The poor diffusion rate can be explained by economic aspects, the 4th subplot shows the 'costs saved' reaching negative values, meaning households would lose money by adopting solar PV in this scenario. Without policy support the installations are expensive due to the 21% BTW tax, and no feed-in tariff means any energy generated by households that they do not consume themselves is not compensated at all, not even by a return fee. This economic issue is exacerbated by the low electricity price of 2021 of 0.134 euro/kWh, leading to lower revenue of the solar PV installation. The electricity generated by the households is valued at this low electricity price, resulting in the households not being able to recoup the high upfront investment. In short, it is not economically attractive for households to adopt solar PV in this scenario, and this is clearly reflected in the poor diffusion rate. Nevertheless, a small fraction of the population still adopts solar PV due to their personal beliefs and attitudes. Despite adoption not being economically attractive for households, the environmental benefits still remain, indicated by the roughly 1.1 ktonnes of CO2-emissions prevented every year after PV diffusion reaches saturation. Base case A is the only experiment where it is not economically efficient for households to adopt solar PV, therefore the results cannot be interpreted with regards to the attitude-behaviour gap.

7.3.2. Base Case B (E3)

Base case B aims to accurately reflect the current situation in The Netherlands. In the current Dutch policy landscape households receive a tax-rebate of 21% (*BTW-aftrek*) of their total installation costs and receive a feed-in tariff for the energy they generate and supply back to the grid. This scenario is used in later experiments to analyze the impact of phasing-out the two aforementioned policies, by comparing those experiments to this base case scenario. In figure 22 the model results of 100 repetitions are displayed.

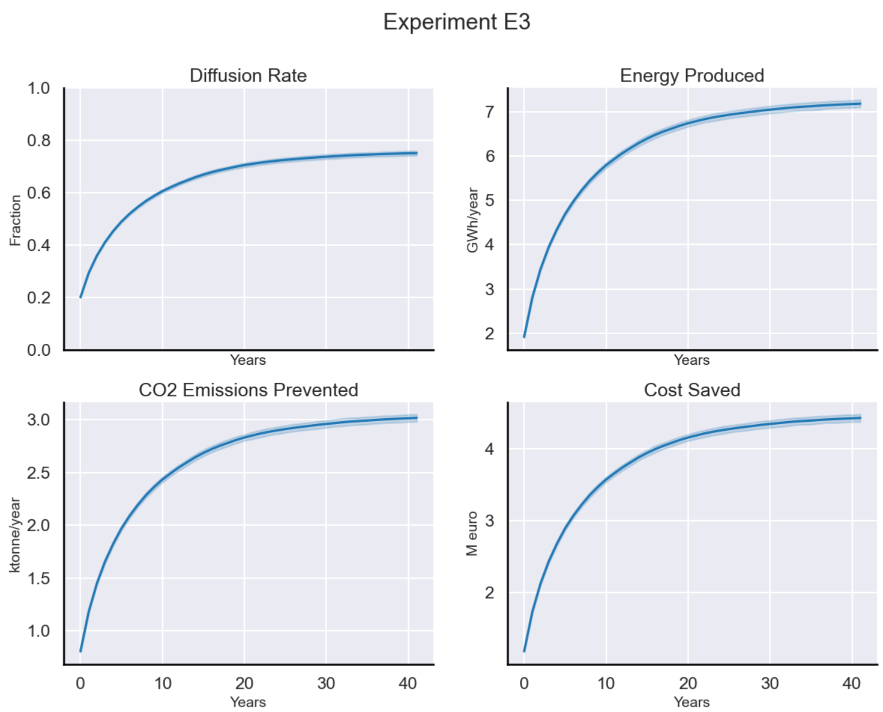


Figure 22
Key performance indicators for 100 repetitions of experiment E3.

A diffusion rate of 75.1% underlines the strong effects of current policies in The Netherlands have on the household adoption of solar PV. The results of this experiment indicate that it has more than double the diffusion rate of experiment E2, with 75.1% and 27.7% respectively (figure 23). Significant energy costs are saved by decentralized household generation, roughly 4 million euros over 40 years. CO2-emissions are reduced significantly by 3.0 ktonnes per year at the peak, when the technology diffusion is saturated in later timesteps.

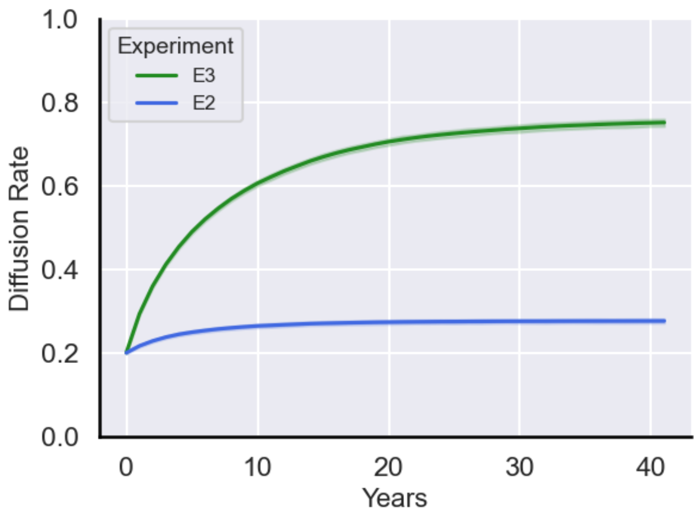


Figure 23
Diffusion rate comparison for experiment E2 and experiment E3.

The speed at which the technology diffuses throughout the population varies, with saturation points being reached at different points depending on the experiment. The saturation point of experiment E2 is at 10 years, compared to a saturation point of roughly 35 years in experiment E3.

The mean weights of the households that choose to adopt solar PV changes throughout the diffusion process as illustrated by figure 24. From start to finish, the adopters' mean social weight increases (+0.026), the environmental weight decreases (-0.016), and the economic weight decreases (-0.010). Demonstrating that earlier adopters value environmental and economic utility above social utility. Note that while it may be hard to see, the mean adopter weights show a higher standard deviation in the later timesteps, because most households adopt in the first 10 years. Therefore, later datapoints are based on less observations, and thus vary more compared to the smoother earlier observations.

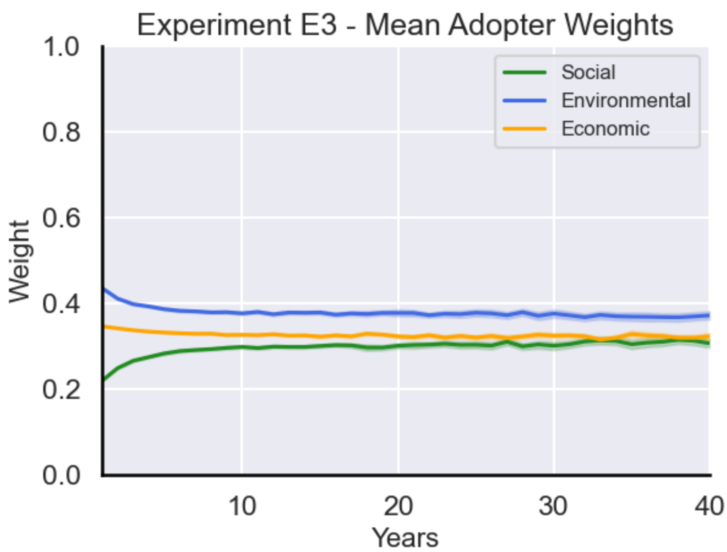


Figure 24
Average of the weights of households that choose to adopt solar PV in that specific timestep.

7.4. Salderingsregeling Phase-out (E4)

The proposed phase-out of the *salderingsregeling* would gradually reduce the amount of electricity households can supply back at full price, from the current 100% to 0% in 2031 (see table 1). Three scenarios are explored in this experiment, the phasing out of the *salderingsregeling* with a flat return fee (E4a), a second scenario where the *salderingsregeling* is phased out but an 80% return fee remains in place (E4b), and a third scenario with instant discontinuation of the *salderingsregeling* (E4c). These experiments are compared to base case scenario B (E3). The financial situation for adopters of solar PV under different scenarios of the *salderingsregeling* is shown in table 9.

Table 9
Salderingsregeling scenarios and financial compensation received.

Salderingsregeling	Experiment	Personal consumption (75%)	Overgeneration (25%)[4]
Current situation	E3	Full price[a]	Flat return fee[b]
Phase-out	E4a	Full price[a]	Full price → Flat return fee[bc]
Phase-out with 80% return fee	E4b	Full price[a]	Full price → >80% of electricity price[c]
No salderingsregeling	E4c	Full price[a]	No compensation

[a] *No 'real' financial compensation is received, instead electricity costs are avoided.*
[b] *Flat return fee depends on energy provider, currently around 0.09 €/kWh (Milieu Centraal, 2022).*
[c] *Gradually declines as shown in table 1.*

The results show significant differences in diffusion rates between the different scenarios (figure 25). The first thing to note is that the diffusion rate of E3 is low than E4b. The base case B (E3) and phasing out with a minimum 80% return fee (E4b) scenarios reach a diffusion rate of 75.1% and 84.7% respectively. This can be explained by the electricity price of 0.134 euro/kWh and the current flat return fee of 0.09 euro/kWh in base case B. Currently, Dutch households receive a flat return fee for the electricity they 'overgenerate'[4] and supply back to the grid, this is reflected in experiment E3. In the proposed phase-out of the *salderingsregeling* with a minimum 80% return fee (E4b) the return fee is 80% of the electricity price, resulting in a compensation of 0.107 euro/kWh, very close but slightly higher than the current flat return fee of 0.09 euro/kWh. This is reflected in the slightly higher diffusion rate of E4b.

If the electricity price were higher, the return fee would scale accordingly, and will result in a situation where the proposed phase-out with 80% return fee is more economically beneficial for PV adopters than the current flat return fee (see section 7.6 for experimentation with high energy prices).

[4] Households may generate more energy than they consume. If a household generates 3000kWh but only consumes 2500 kWh, then 500 kWh would be 'overgenerated' and compensated with a flat return fee.

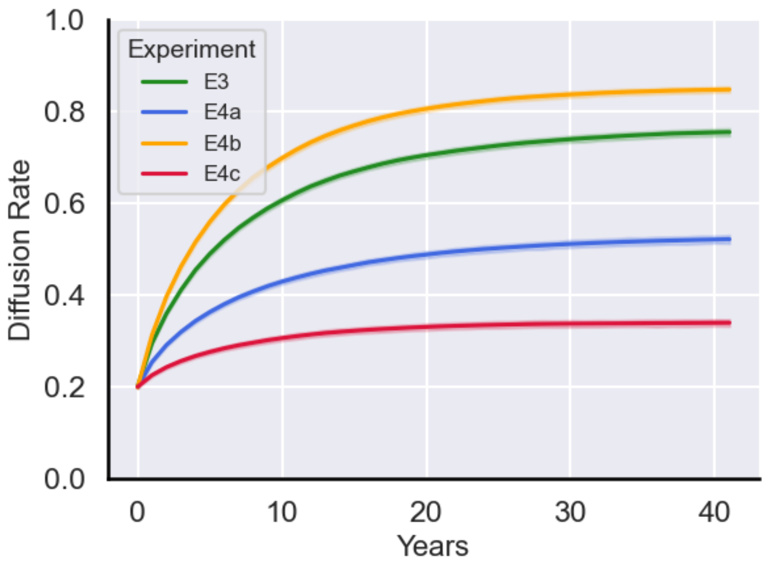


Figure 25
Diffusion rate comparison for experiment E4, compared to base case B (E3).

Gradually phasing-out the *salderingsregeling* results in a significantly lower diffusion rate of 52.1%. Phasing-out the *salderingsregeling* would limit households to a flat return fee—lower than the electricity price—for the electricity they overgenerate and supply back to the grid. The flat return fee is currently around 0.09 €/kWh, depending on the energy provider (Milieu Centraal, 2022), but this may see reductions in the future that could hurt PV adoption without *salderingsregeling* even more.

A situation where the *salderingsregeling* is not present can be found in experiment E4c. Here households do not receive any compensation for the energy they generate and do not consume themselves. The diffusion rate in this scenario is limited to 33.9%, a significant decrease compared to the current situation or phase-out with 80% return fee. Without compensation it is less economically attractive for households to adopt solar PV. Nevertheless, 0.46 million euros of costs are saved, and a CO2 reduction of 1.365 ktonnes/year is achieved in later years, the environmental benefits are there but not as strong as they could be compared to E4b with 3.400 ktonnes/year when saturated.

7.5. Tax Rebate discontinuation (E5)

Currently, households and small businesses in The Netherlands have the right to a tax rebate when investing in solar PV installations for the first time (Rijksoverheid, 2022). This tax rebate is equal to the BTW-value of 21% of the total installation price, and drastically reduces the payback period of solar PV installations in The Netherlands and the high upfront cost normally associated with solar PV installations. This experiment explores two possible scenarios where the tax rebate is halved (E5a) and discontinued completely (E5b), compared to base case B (E3). Results are displayed in figure 26 below.

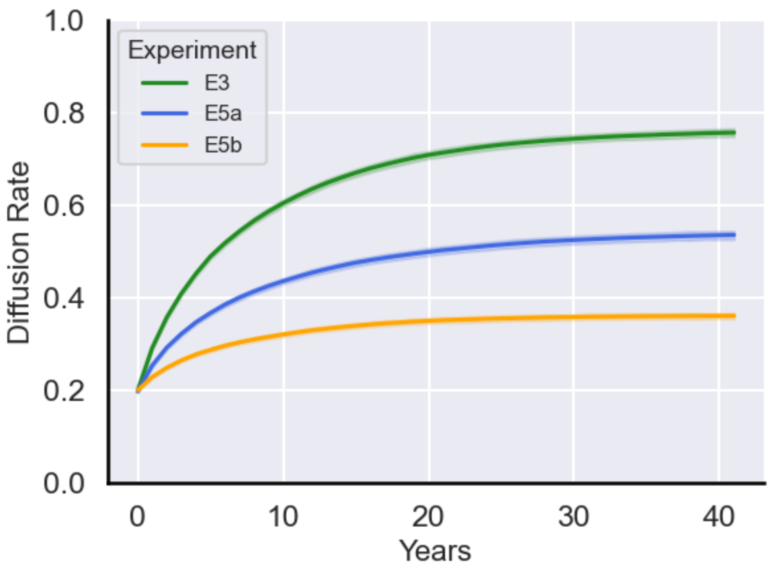


Figure 26
Diffusion rate comparison for experiment E5, compared to base case B (E3).

Diffusion rates are significantly lower when the tax rebates are discontinued. The current 21% tax rebates (E3) stimulate the rate of adoption to 75.1%, while a 10% tax rebate (E5a) is linked to a diffusion rate of 53.6%, and no tax rebates (E5b) lowers the rate of adoption even further to 36.1%. Decreasing the upfront costs of solar PV installations decreases the payback period, making solar PV more economically attractive for households, allowing them to recoup their investment sooner.

The results are similar to the previous experiment where the effects of phasing-out the *salderingsregeling* were explored (E4), discontinuing current policy interventions results in a lower diffusion rate. However, scenarios without *salderingsregeling* (E4c) had stronger effects on the diffusion rate than the discontinuation of tax rebates (E5b), with diffusion rates of 33.9% and 36.1% respectively.

7.6. High Energy Price (E6)

Considering the current energy crisis in Europe due to the invasion of Ukraine, scenarios with high energy prices are explored in the model. A range of prices from the historic price of 2021 (CBS, 2022a) to the current price of approximately 0.77 €/kWh (Essent, 2022) is considered in experiments E6a to E6e. These experiments are added to evaluate the robustness of policy interventions in extreme situations.

First, the impact of a high electricity price in base case B is considered. As is illustrated by figure 27 the model is sensitive to electricity prices. The difference in electricity costs between base case B (E3) and E6a is only 0.066 €/kWh (0.134 vs 0.2 €/kWh), yet the diffusion rate shows a large increase: 75.1% vs. 98.4%. In scenarios where the electricity price is even higher (E6b-E6e) the diffusion rate reaches the same saturation level, except the speed of diffusion is slightly faster, meaning the saturation level is reached faster.

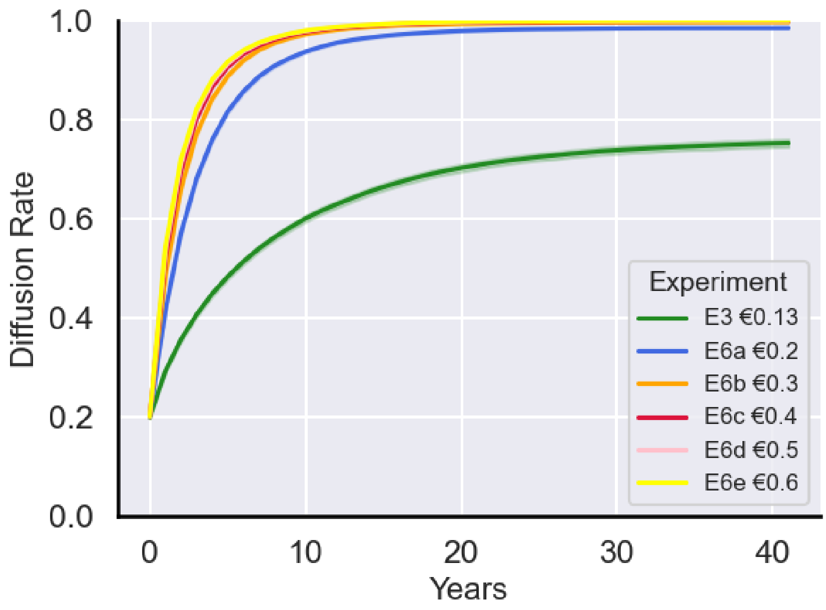


Figure 27
Diffusion rate comparison for experiment E6, compared to base case B (E3).

The total costs saved by the households is highly dependent on the electricity price (figure 28). When households install solar PV they prevent spending on electricity costs, thus increasing the total cost saved due to the electricity cost saved. The increase in costs saved between experiments scales roughly linearly with the increase in electricity price.

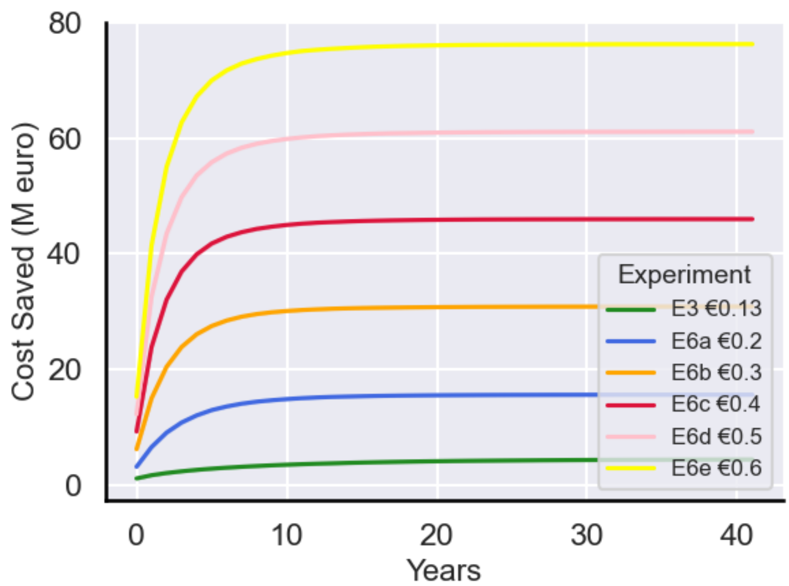


Figure 28
Total cost saved comparison for experiment E6, compared to base case B (E3).

Both policy interventions—the *salderingsregeling* and tax-rebates, tested in E4 and E5 respectively—are explored in a high energy price scenario to evaluate the robustness of these policy interventions under varying conditions, illustrated in figure 29. In this experiment the electricity cost is set to 0.2 €/kWh because the impact of the policy interventions in a scenario with electricity prices set to 0.5 €/kWh were undiscernible, since the adoption rate was extremely high under all conditions.

Even in a scenario with a price of 0.2 €/kWh the economic benefits for households are so significant that the effects of the *salderingsregeling* are barely noticeable, demonstrated by the overlapping green/blue and orange/red lines. The *salderingsregeling* still has a small effect on the diffusion rate, but to a lesser extent compared to the tax rebates as illustrated by figure 29. The small effect of the *salderingsregeling* is noticeably weaker than the effect under standard circumstances seen in experiment E4.

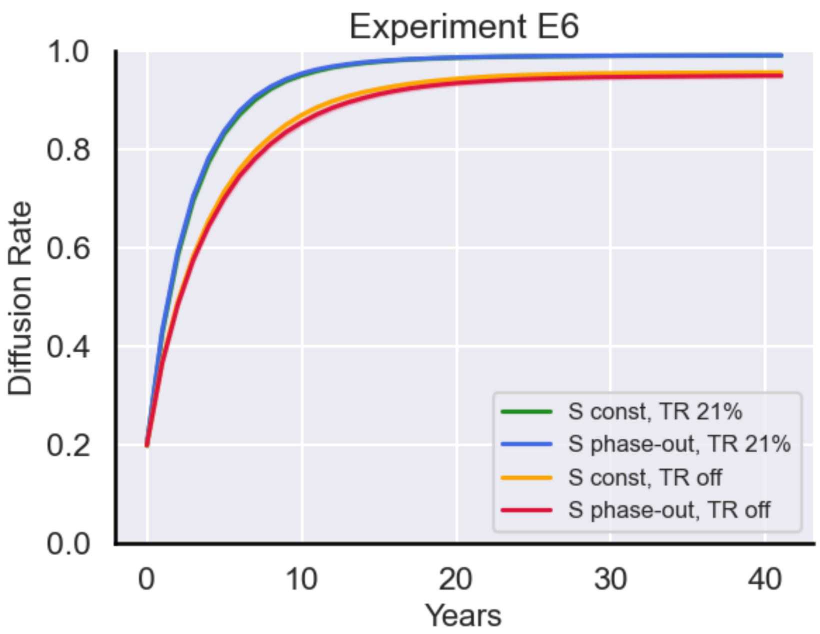


Figure 29
Comparison of policy intervention effects in a high energy price scenario. The salderingsregeling is represented by 'S', the tax-rebates by 'TR'.

7.7. Sensitivity Analysis

Systematically evaluating the model sensitivity is necessary but also challenging for ABMs (Van Dam et al., 2013). The sensitivity analysis is performed on input parameters of the model that are uncertain. The uncertainty in the outcomes is analyzed to see how strongly this uncertainty can be apportioned to the uncertainty in input parameters (Iwanaga et al., 2022). The GSA is performed similarly to how it is performed in section 7.2, except with different input parameters and not time dependent.

The input parameter setup is shown below (table 10). Parameters that are not displayed in the table are set identical to the base case B scenario (E3). Instead of changing parameters one by one, a global sensitivity analysis (GSA) is performed to capture the model behaviour across the full parameter space (Saltelli et al., 2008). GSA is useful in capturing the interactions between input parameters, represented by the first-order sensitivity index (Jaxa-Rozen & Kwakkel, 2018).

Table 10
Sensitivity analysis input parameter setup. Saltelli's extension of the Sobol sequence may take any value between the value ranges shown in the table.

Parameter	Value
surface_to_roof_area_ratio	[0, 1]
electricity_cost	[0.1, 0.6]
household_consumption_factor	[0, 1]
interest_rate	[0, 0.05]
WS_K	[2, 6]
WS_Beta	[0, 0.5]
pv_irradiation_factor	[0.8, 1]
pv_cost_per_kwp	[1200, 1600]
pv_peak_power	[180, 260]
pv_performance_ratio	[0.7, 0.9]
pv_lifetime	[20, 30]
pv_co2_per_kwh	[0.32, 0.52]

Twelve input parameters are tested with 256 runs, resulting in a sample size of 6656 (n(2p+2)). As stated before in section 7.3.1, this sample size is relatively small due to computation limitations and will result in larger confidence intervals for the Sobol indices than desired, especially for the first-order sensitivity indices.

The *initial_pv_percentage* input parameter is not considered because it has a 1:1 relation the diffusion rate. In a situation where initially 100% of the households have solar PV installed, the diffusion rate would also be 100%. The recorded output is the final diffusion rate KPI at timestep 40. Other input parameters may take any values between the indicated value range in table 10.

7.7.1. Sensitivity Analysis Results

Figure 30 illustrates the sensitivity of the output rate to each input parameter. The scatterplots with Pearson correlation linear trendlines indicate the sensitivity for each of the 12 input parameters. A negative trendline indicates a lowered diffusion rate when the input parameter is increased, and vice versa.

The electricity price and household consumption factor are the two input parameters that are responsible for the largest variance in the model output. As shown by figure 31 these two parameters contribute to roughly 80% of the output variance alone, and roughly 50% when accounting for interactions with other input parameters. Even minor changes in either of these two input parameters affect the diffusion rate significantly.

The economic utility factor of TPB is dependent on the payback period of the solar PV investment. With a higher electricity price, the payback period is reduced, therefore increasing the economic utility and the adoption rate. Households are heterogenous and do not respond identically to the economic utility factor, but all of them do to some extent.

The household consumption factor is the fraction of electricity that the households generate and also consume themselves. In the model the households are assumed to consume 75% of the electricity they generate themselves. This is an important aspect for the discounted cashflow calculations (due to the *salderingsregeling*) and thus affects the length of the payback period and the economic attractiveness of investing in solar PV. This value is chosen because households know that the *salderingsregeling* will be phased out, nudging them to buy solar PV installations that are more appropriate for their own consumption. Households know they may not get a return fee for electricity they return to the grid in the future, therefore adopting a larger PV installation is a gamble and households are more likely to opt for smaller PV installations. Unfortunately, the results of the sensitivity analysis indicate that the household consumption factor assumption has a significant influence on the model outputs, this is not ideal because it undermines the robustness of the conclusions. Better and more widely available data in this area could help refine the model results and increase the robustness of the model.

Due to the low n number used for sampling (n=256) the 95% confidence intervals are relatively large, as indicated by the error bars in figure 31. Additionally, because the two aforementioned input parameters contribute to such a large amount of output variance the contribution of the other factors seems less than it may really be. The full table of global sensitivity analysis results may be found in Appendix E. The sensitivity analysis is performed on the end state of the model simulation.

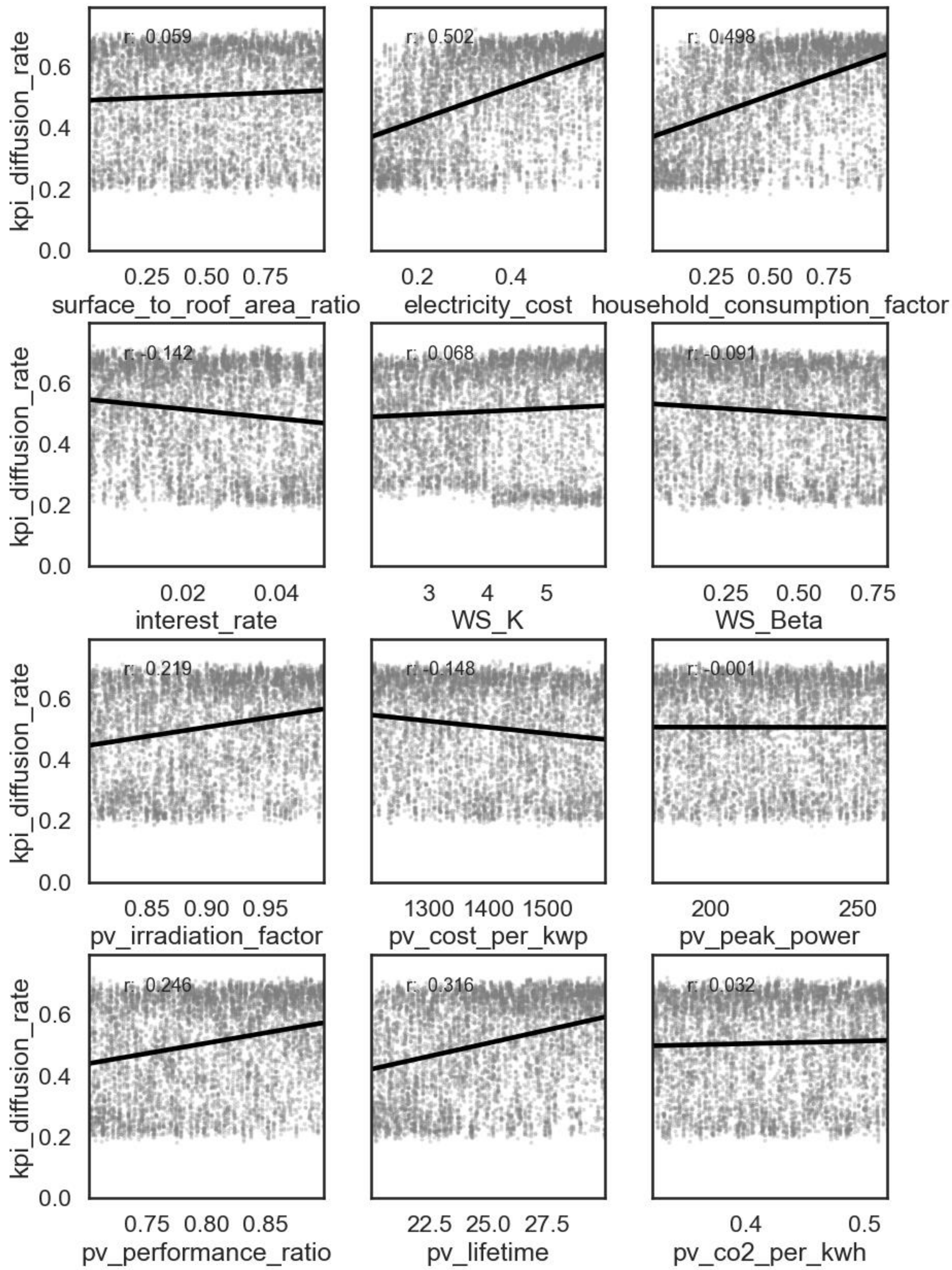


Figure 30

Scatter plots of the twelve input parameters with linear trendlines (Pearson correlation) displaying the sensitivity of the diffusion rate to each input parameter in the end state.

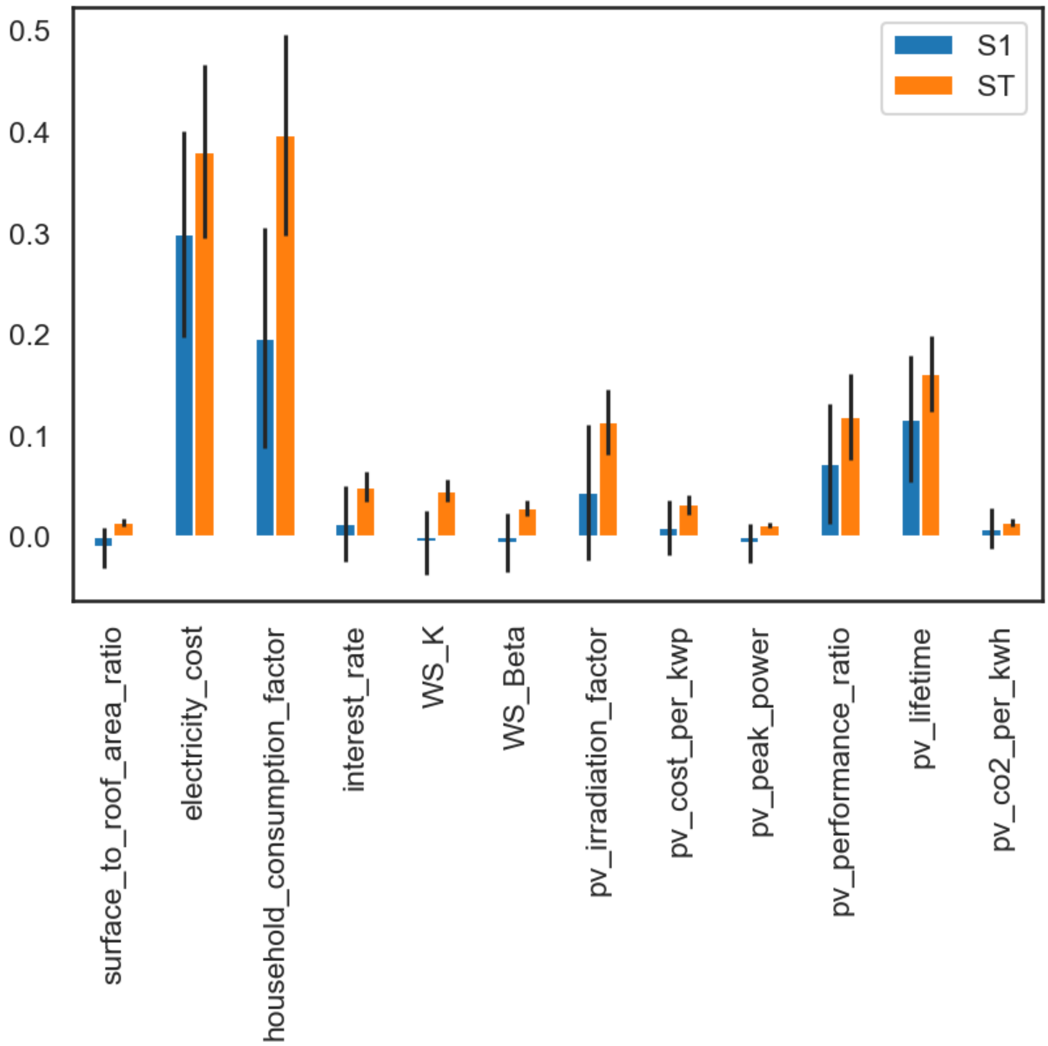


Figure 31
Bar graph illustrating the first-order Sobol (S1) and total Sobol indices (ST) of 6656 samples with 95% confidence interval error bars.

7.8. Conclusion

This chapter showed the results of the experiments, based on the experimental design presented in section 4.4. The KPIs were presented and comparisons between experiments illustrated with the use of various graphs. A time-dependent global sensitivity analysis was performed to illustrates the share in variance explained by each psychological factor, thus demonstrating to what extent these factors contribute towards the emergence of the attitude-behaviour gap in Dutch households, thereby addressing sub question 4. Furthermore, relevant Dutch policy interventions such as the phasing-out of the *salderingsregeling* and tax-rebates were considered, to analyze how these can contribute towards closing the attitude-behaviour gap, to address sub question 5. Lastly, the global sensitivity analysis was performed on the input parameters that are uncertain. Demonstrating that the interest rate and the amount of non-local connections had significant impact on the diffusion rate of solar PV, underlining the importance of both economic and social aspects in the model.

8 Analysis & Discussion

Before the model results are analyzed, the model validation is performed in this chapter. Model validation regarding the model purpose and a quantitative validation with survey data are performed. Secondly, the model results presented in the previous chapter are analyzed and discussed. Lastly, the trade-offs present in the model are discussed, and the limitations of the research are considered.

The following sub questions are addressed in this chapter:

SQ4: To what extent does each identified factor contribute towards shaping the attitude-behaviour gap?

SQ5: What are policy interventions that can contribute towards closing the attitude-behaviour gap, and what is their effectiveness?

SQ6: How can the results of this study aid policymakers in closing the attitude-behaviour gap?

8.1. Model Validation

Before the model validation is conducted the purpose of the model will be reiterated. This research aims to explore the attitude-behaviour gap in a household energy consumption context. Household decision-making is studied, with the goal of understanding what factors may cause the attitude-behaviour gap of diverse individuals. To ultimately close the gap by lowering the barriers to adoption with targeted policy interventions.

The ABM used in this research is an exploratory model; it is meant to support conclusions based on a limited number of experiments (Bankes et al., 2013), it is not meant for predicting the future. The first application of the model is exploring what contributes towards the emergence of the attitude-behaviour gap. The second application of the model is ex-ante policy intervention exploration, for evaluating policy impacts to judge their effectiveness on closing the attitude-behaviour gap in diverse individuals.

This is relevant for the model validation because this represents a challenge, due to the many relevant components of the system and the forward-looking nature of the sub questions (Chappin et al., 2019). Traditionally validation is performed by comparing reality with the model results, similar to how validation is performed in the natural science. However, in this ex-ante exploratory research there exists no feasible method of collecting observed reality data (looking into the future), meaning validation is impossible in the traditional sense (Nikolic & Ghorbani, 2011). It is not feasible to verify the model outcomes, because the model includes behavioural, social, and policy aspects without real available validation data (Chappin et al., 2019).

8.1.1. Quantitative validation with survey data

This means other methods of validation must be performed, such as qualitative and quantitative validation based on the available survey data. The issue with using empirical survey data for validation purposes is the lack of longitudinal data. The survey was conducted once, without follow-up to check whether the respondents actually adopted solar PV installations, rendering validation with survey data questionable. Nevertheless, the alternative method for conducting a quantitative validation—with the survey data, despite it not containing longitudinal data—is possible due to the inclusion of the following survey question:

"When did you apply your energy production (e.g. install solar panel/solar thermal/turbines) or do you plan to apply it?"

For this survey question, respondents could pick four answers: (1) more than 6 years ago, (2) in the past 5 years, (3) in the coming year, (4) in the next 3 years. The responses combine both behaviour in the past (1 & 2) and intention (3 & 4). While the latter two responses to this question are considered intention and not actual future behaviour, it may be considered a proxy and is the only way to perform quantitative model validation with the limited survey data. This proxy method comes with caveats, such as the response bias (more specifically social-desirability bias) inherent in survey question responses. Respondents tend to be dishonest and give socially acceptable answers (Niamir et al., 2020), despite strict measures being taken to prevent response bias in the survey (refer to section 5.3.1).

The quantitative model validation with the survey data is performed by running the simulation model, identifying the households that have declared their intention to adopt solar PV in the near future (households with responses 3 & 4) and recording whether they have adopted solar PV at timestep 1 and timestep 3 respectively, as they declared in their survey response. Unfortunately, the majority of respondents left this survey question empty. Only a small fraction of respondents (n=7) indicated they have an intention to install solar PV in the coming year, or in the next 3 years (n=25). Furthermore, with the combinatorial optimization method of agent initialization it does not guarantee the exact amount of 32 households to be present in the synthetic population. Due to this, only the households that indicated they have an intention to install solar PV in the next 3 years are used for validation purposes.

With this in mind, the validation results should be taken with a grain of salt. There is a large standard deviation (0.107) in the validation results due to the issues discussed above, regardless of the number of model repetitions. Additionally, the validation results are sensitive to the combinatorial optimization seed that produces the synthetic population, because the fraction of households on which validation may be performed is so small (n=25) compared to the whole population of 1035 households, resulting in the CO sampling impacting the number of households on which validation may be performed. The quantitative validation concludes that on average 51.6% of the households in the validation sample that indicated in the survey the intent to adopt solar PV in the coming 3 years, also adopt solar PV in the model.

8.2. Analysis of Model Results

The overall goal of the experimental design was to show the emergence of the attitude-behaviour gap, determine what factors contribute towards the emergence of the gap, identify what the barriers to adoption are, and ultimately explore policy interventions that may aid in closing the gap by targeting these barriers to adoption. Experiment E1 featured the time-dependent global sensitivity analysis to determine what factors contribute towards the emergence of the attitude-behaviour gap. Further experiments analyzed the discontinuation of policy interventions such as the Dutch *salderingsregeling*, a type of feed-in tariff, and tax-rebates. Finally, the robustness of these policy interventions was analyzed in scenarios with high energy prices, as we are experiencing now with the ongoing European energy crisis due to high gas prices caused by the invasion of Ukraine.

The GSA was performed with a set of input parameters that are key to the model behaviour, representing psychological factors that impact human decision-making, such as attitudes, biases, and knowledge. GSA was performed to show what factors have the strongest influence on the diffusion process and the emergence of the attitude-behaviour gap, and how first-order interactions between model elements may influence the simulation model results.

8.2.1. Social Effects

Results from the GSA have demonstrated that social effects have a strong impact on the emergence of the attitude-behaviour gap (figure 17) and diffusion rates in general. This agrees with research demonstrating social dynamics are related to the diffusion of solar PV systems (Jager, 2006; Maya Sopha et al., 2011; Shum, 2010). Households consider the perception about the attitude of others and social expectations to varying extents. This leads to social pressure and social comparisons (Frederiks et al., 2015), especially with trusted connections that display strong age, income, and education parity. In early stages of simulations with low initial PV adoption percentages (i.e. all experiments) the social effects act as a barrier to adoption, the pressure to stick to the status quo is higher than the social pressure to adopt solar PV. In line with Rogers' (1995) conclusion, early adopters in the model generally install solar PV due to personal reasons; economic or environmental. While later adopters tend to be more socially oriented and are encouraged by social effects when a large part of the population has already adopted solar PV (figure 24).

Network effects also play a role in the diffusion process due to their role in governing the spread of information between households, as shown by the sensitivity of the model (figure 30 & 31) to the Watts-Strogatz algorithm K (*WS_K*) parameter that determines the average node degree, that represents the number of social connections the household has. Simulation runs where households have more connections show a decreased diffusion rate. A potential justification could be a feedback loop caused by the low social pressure to adopt (due to the increased number of connections to mainly households who have not adopted solar PV), leading to fewer adoptions, ultimately keeping the social pressure low. Less pressure towards PV adoption from cliques in early stages of the simulation results in fewer PV adopters, leading to less social pressure to adopt when the technology is more established in later stages of the simulation, resulting in lower final diffusion rates of solar PV systems seen in scenarios with a high *WS_K* parameter.

Additionally, the survey does include questions on the social factors and subjective norms but does not include data on the social network structure of households. This resulted in the social network being structured based on methods and parameters seen in existing literature, weakening the results of the model regarding social effects and the impact of subjective norms.

8.2.2. Economic Aspects

When combined, economic aspects contribute towards the attitude-behaviour gap to a greater extent than social effects, especially in later stages of the simulation (figure 18). Model results demonstrate that for the households, financial aspects remain important for the choice of whether to adopt solar PV or not. This is underlined by the model sensitivity (figure 30 & 31) to the interest rate and electricity price, that strongly influence the payback period of a solar PV installation. Note that households have a heterogenous sensitivity towards the economic aspects of solar PV based on the survey data; some households put more significance on the economic factors than others.

Higher interest rates lead to a longer payback period for the solar PV system. With higher interest rates households are less likely to adopt solar PV (figure 30 & 31), as the economic benefits are smaller. In the model households perform discounted cash flow calculations to determine the payback period, but in reality people tend to be short-sighted and perceive things that are further away in time as less important, referred to as ‘temporal discounting’ (Frederiks et al., 2015). This implicates that the model results may be overshooting the effects of interest rate on the adoption of solar PV.

Electricity price has a large influence on the diffusion rate as shown by experiment E6 (figure 27). With a higher energy price, the households who have adopted solar PV gain a larger benefit because they save more electricity costs compared to households who do not have solar PV systems. The difference in electricity costs between base case B (E3) and E6a is only 0.066 €/kWh (with costs of 0.134 vs 0.2 €/kWh), yet the diffusion rate shows a large increase: from 75.1% to 98.4%. In scenarios where the electricity price is even higher (E6b-E6e) the diffusion rate reaches the same saturation level, except the speed of diffusion is slightly faster, meaning the saturation level is reached faster. Electricity price is a large contributor towards the economic utility, and thus the attitude-behaviour gap.

The economic uncertainty for households represents the lack of information regarding the future. Households cannot be confident in their actions when there remains uncertainty in future energy prices, uncertainty in interest rates, and uncertainty in phasing out or introducing new policy interventions. These aspects act as barriers to adoption for households when they consider the economic utility of solar PV, they support the households’ decision to stick to the status quo, to not adopt solar PV. The economic uncertainty contributes towards the attitude-behaviour gap significantly with a total Sobol index of 0.42 (figure 18).

The contribution of economic uncertainty towards the attitude-behaviour gap can perhaps be explained by risk-averse nature of human decision-making. People tend to be “more risk averse-when faced with certain (high probability) gains or uncertain (low probability) losses, but more risk- seeking when faced with certain losses or uncertain gains” (Frederiks et al., 2015; Kahneman & Tversky, 1979; Tversky & Kahneman, 1992). When people are presented with the choice of adopting solar PV, they tend to be irrationally risk averse in their actions, despite the high probability gains from electricity cost savings and uncertain low probability losses from changes in the electricity price or policy interventions.

8.2.3. Influence of PBC

Two time-dependent GSA have been performed with different PBC operationalizations. One with a probabilistic income barrier (figure 17), and a second with a threshold income barrier (figure 20). As illustrated by these graphs the PBC component contributes towards the attitude-behaviour gap more significantly when it is modelled as a threshold income barrier (Sobol indices of 0.09 vs 0.45 at timestep 1). When PBC is operationalized as a threshold it acts as a ‘hard’ barrier, households with incomes below the threshold will never pass the affordability barrier and therefore never consider the utility of adopting solar PV. With a probabilistic implementation of perceived behavioural control the low-income households have a reduced chance to pass the affordability barrier, but over the span of 40 timesteps there is still a chance of them adopting solar PV. This is not the case with the threshold operationalization, resulting in the threshold value contributing towards the output variance roughly five times as much when compared to the probabilistic operationalization.

8.3. Analysis of Policy Interventions

Two experiments were conducted to explore the impact of phasing-out policy interventions on the diffusion rate and the emergence of the attitude-behaviour gap. In experiment E4 the phasing out of the *salderingsregeling* is explored, and in E5 the discontinuation of the current tax-rebates.

Three different *salderingsregeling* scenarios were explored to analyze the effects of the potential phase-out on the adoption of household solar PV: the phasing out of the *salderingsregeling* with no return fee (E4a), a second scenario where the *salderingsregeling* is phased out but an 80% return fee remains in place (E4b), and a third scenario with instant discontinuation of the *salderingsregeling* (E4c). The model demonstrates that the *salderingsregeling* is an effective incentive for households to change their behaviour due to the increased economic benefit when adopting solar PV. Changes introduced by the *salderingsregeling* regardless of implementation ultimately shorten the payback period of the solar PV installations, as is reflected in the adoption rates in scenario E4a and E4b (52.1% and 84.7%) compared to E4c (33.9%) in figure 25. These results underline that cost remains an important barrier that contributes to emergence of the attitude-behaviour gap as discussed in section 8.2.2. Without policy that ensures compensation for energy the households generate (but do not consume themselves) and return to the grid, there is more investment risk involved and it is less economically attractive for households to adopt solar PV.

Tax rebates showed a similar increased attractiveness for households to invest in solar PV. The experiment explored two different scenarios where the tax rebate is halved (E5a) and where the tax rebates are discontinued completely (E5b), compared to the base case scenario with 21% tax rebates (E3) as shown in figure 26. Diffusion rates are significantly lower when the tax rebates are discontinued, with 53.6% diffusion in scenario E5a and 36.1% diffusion in scenario E5b. Decreasing the upfront cost of solar PV installations decreases the payback period, making solar PV more economically attractive for households, allowing them to recoup their investment quicker. Additionally, it lowers the high upfront cost barrier that contributes to the attitude-behaviour gap.

The robustness of both policy interventions in scenarios with high energy prices is analysed in experiment E6. Model results indicate that in scenarios with electricity prices above 0.2 €/kWh the economic benefits for households are so significant that the effects of the *salderingsregeling* are barely noticeable, and the tax rebates are the main determinant of the diffusion rate (figure 29).

From the model results the conclusion can be drawn that the Dutch policies are effective in making solar PV more appealing for small-scale users, increasing adoption rates significantly by lowering the economic barriers for households. Even for households that may hold positive attitudes towards the environment, the economics remain an important aspect that ultimately determines their behaviour, and by structuring policies that specifically address these economic barriers the attitude-behaviour gap can be shrunk.

In this model only financial policy interventions were considered. The spotlight is often on financial instruments, but information-based policy instruments may aid in improving knowledge or attention to an issue or a technology as well. Consumers may not be aware that their consumption directly affects the environment. Additionally, complete information on the energy-efficient technology and performance of a product aids the consumer in estimating the costs and benefits properly. Financial instruments may even be counterproductive in achieving the ideal behaviour, highlighting the boundedly rational human behaviour not in line with the rational choice model (Frederiks et al., 2015). This is because interventions focused on behaviour are less likely to trigger 'rebound effects' (Jensen et al., 2016) where improvements in efficiency lead to cost reductions allowing consumers to buy and use more of the product in return.

8.4. Trade-offs

In the model results several trade-offs have been identified. One of the trade-offs relates to equity concerns of financial policy interventions. Public spending on policy interventions should not favour a set of households that already possess the means to invest in solar PV themselves, instead the focus should be on low-income households to maintain a level of equity. The OECD (2014) recommends financial instruments to support low-income households likely because the consumers who adopt solar PV are much wealthier than average consumers (Rai & McAndrews, 2012). The model results indicate that the high upfront costs pose a barrier to adoption and households are sensitive to economic incentives, especially low-income households that are more heavily impacted by this barrier. This is a relevant topic for solar PV especially, since low-income households are more likely to rent their residence than high-income households, and households that rent are less likely to invest in energy efficiency and renewables (Ameli & Brandt, 2015). This is the result of a split incentive problem in a rental situation, where real estate owners should be able to adjust their rental prices if they invest in energy efficient technologies, as the benefits of such an investment lie with the renter who will see a decrease in their energy bill (Ameli & Brandt, 2015). Therefore, the equity of incentivized adoption should be considered, and constantly evaluated to ensure the distribution of benefits of public spending occurs in a fair manner.

A second issue for policymakers is the trade-off between stimulating adoption and undesired side effects. Overstimulating decentralized energy generation may lead to network congestion; more issues on the low voltage distribution network that is already struggling with network congestion, leading to long waiting lists of companies that want to be connected to the electricity grid (NOS, 2022b).The Vereniging Nederlandse Gemeenten (VNG), a group of Dutch municipalities, already launched a motion to discontinue the *salderingsregeling* due to local network congestion (van Gastel & de Jonge Baas, 2022). Furthermore, overstimulating adoption of solar PV leads to the prosumers returning electricity to the grid at the same time during sunny periods, decreasing the return fee they receive, thus decreasing the economic attractiveness and lengthening the payback period.

Unfortunately, the results from the model do not consider the cost of policies, so it cannot be concluded whether the tested policies were cost-effective due to lack of information on policy costs. However, there is an obvious trade-off between the stimulation of solar PV adoption and the cost to the taxpayer. Costs should be in line with the societal benefits.

8.5. Conclusion

The model validation presented a challenge because traditional validation could not be performed due to the lack of available validation data. Ideally the validation could be performed with longitudinal survey data, but this data was not available. Therefore, a quantitative model validation with cross-sectional survey data was conducted. The model results underlined the importance of economic barriers, especially economic uncertainty, in the emergence of the attitude-behaviour gap. The analysis of the policy interventions demonstrated similar conclusions, with financial policy instruments having significant impact on the diffusion rate of solar PV and the emergence of the attitude-behaviour gap. The GSA demonstrated that the contribution of factors did not significantly vary or evolve over time. Lastly, the trade-offs were discussed between public spending and equity concerns, stimulating adoption and network congestion, and stimulating adoption and taxpayer costs.

9 Conclusion & Recommendations

In this chapter the study is concluded by addressing the sub questions and main research question. The main research question was posed in section 3.2 and the sub questions were posed in section 3.3. The experimental design was created so the model results could address the research questions.

9.1. Main Research Question

In this research an empirically grounded agent-based simulation (ABM) simulation approach with theoretical foundation was used to study household decision-making, with the goal of understanding what factors may cause the attitude-behaviour gap of diverse individuals. Ultimately, to close the gap by lowering the barriers to adoption with policy interventions. The main research question being addressed is:

To which extent can different psychological factors influence the emergence of the attitude-behaviour gap in household energy consumption, and what policy interventions can be employed to close the gap?

To address this research question an ABM simulation study has been successfully conducted. An empirically grounded, theory based, ABM model was developed to simulate the diffusion process of solar photovoltaics (PV) in a set of heterogenous Dutch households. The study incorporated various data sources to add a strong empirical foundation to the model, including single-user survey data in a novel combinatorial optimization method for synthetic population generation. The focus of this model was the decision-making behaviour of consumers, using the theory of planned behaviour (Ajzen, 1991) as theoretical foundation to structure the decision-making. Household agents in the model demonstrate satisficing behaviour and myopically choose whether to adopt solar PV or stick to the status quo.

The model results, specifically the time-dependent global sensitivity analysis results, illustrate what factors and to what extent these factors contribute towards the emergence of the attitude-behaviour gap. When combined, economic barriers contribute towards the emergence of the attitude-behaviour gap to a greater extent than social factors, especially in later stages of the simulation, when the diffusion process has slowed down and has almost reached saturation. The main economic barriers to adoption are (1) the financial benefits compared to the high upfront cost, and (2) the economic uncertainty regarding the future due to a lack of information. This uncertainty is compounded due to the current Dutch policy landscape, where the controversial phasing-out of the *salderingsregeling* adds an extra layer of uncertainty. When consumers are presented with the choice of adopting solar PV, they tend to be unreasonably risk-averse in their actions, despite the high probability gains from electricity cost savings and uncertain low probability losses from changes in the electricity price or policy interventions, as illustrated by the contribution of economic uncertainty to the emergence of the attitude-behaviour gap.

Nevertheless, the importance of the social factors should not be overlooked. Results from the time-dependent global sensitivity analysis have demonstrated that social effects are not negligible and have an impact on the emergence of the attitude-behaviour gap and diffusion rates in general. Households consider the perception about the attitude of others and social expectation, this leads to social pressure and social comparisons between households, especially with trusted social connections. Results indicate that early adopters in the model generally install solar PV due to personal reasons; economic or environmental. While later adopters tend to be more socially oriented and are encouraged by social effects, when a large part of the population has already adopted solar PV and the social pressure to adopt is higher. Unfortunately, the survey does include questions on the social factors and subjective norms, but does not include data on the social network structure of households. This resulted in the social network being structured based on methods and parameters seen in existing literature, weakening the conclusions of the model on social effects and the impact of subjective norms compared to other factors in the model.

It should be noted that the operationalization of the perceived behavioural control (PBC) component has a significant impact on the model results. When the PBC component is operationalized as a threshold it acts as a 'hard' barrier, households with incomes below the threshold will never pass the affordability barrier and therefore never consider the utility of adopting solar PV. With a probabilistic implementation of perceived behavioural control, the low-income households have a reduced chance to pass the affordability barrier, but there remains a slim chance of them adopting solar PV. This is not the case with the threshold operationalization, resulting in the threshold value contributing towards the output variance roughly five times as much when compared to the probabilistic operationalization. This illustrates that the perception of affordability that is represented by the PBC component has a significant impact on the emergence of the attitude-behaviour gap, but is heavily dependent on the operationalization of the TPB.

The two policy interventions explored in this research—a feed-in tariff referred to as the *salderingsregeling* in The Netherlands, and a tax-rebate referred to as *BTW-aftrek*—are both effective in making solar PV more appealing for small-scale users, increasing adoption rates significantly by lowering the economic barriers for households. Especially in scenarios with high electricity prices (anything above 0.20 €/kWh shows very high rates of adoption), here the economic benefits for households that adopt solar PV are so significant that very high adoption rates are observed. Even for households that hold positive attitudes towards the environment, the economics remain an important aspect that ultimately determines their behaviour, and by structuring policies that specifically address these economic barriers the attitude-behaviour gap can be shrunk. Nevertheless, the cost-effectiveness of these policies was not considered in this research, so there exists a trade-off between public spending and environmental benefits. Public money spent on other policy interventions that protect the environment and promote sustainability may be a better option. This could be the subject of further research focused on the cost effectiveness of policy interventions.

These conclusions should be considered with the following limitation in mind; the main research question considers the attitude-behaviour gap, this implies the dependent variable is behaviour, yet the survey data only measures self-reported intention. Due to the non-longitudinal survey data, it could not be observed whether households actually acted on their good intentions of installing solar PV as they reported in the survey, if they merely remained intentions or translated into observed behaviour. This limitation implies that the gap in this research is the attitude-intention gap, rather than the attitude-behaviour gap. Instead of *action* being measured, it is *expected action*. This means within the model results and conclusions there likely is a discrepancy between the self-reported intention and the observed behaviour. This is a common problem (response bias) and part of a larger debate within social psychology (Armitage & Conner, 2001) and relevant for interpreting the results of this study.

9.2. Addressing Sub Questions

In section 3.3 the six sub questions were introduced that contribute towards addressing the main research question posed in section 3.2. The detailed research activities, research tools used, and deliverables used to address the sub questions are discussed in-depth per sub question in appendix B. The sub questions are addressed below.

9.2.1. Sub question 1

SQ1: What factors are relevant in exploring the emergence of the attitude-behaviour gap?

The scope of the literature review was intentionally broad to capture a wide variety of factors that are relevant to human decision-making behaviour and the emergence of the attitude-behaviour gap, to ultimately identify overarching themes or commonly investigated factors in the literature that are essential components in the socio-technical system.

The relevant factors are sometimes referred to as 'barriers to adoption', as households are often hindered from adopting energy-efficient technologies by these factors, they impede the diffusion process and lead to emergence of the attitude-behaviour gap.

The potential explanations for the energy efficiency gap generally fall into three broad categories: (1) market failures, (2) behavioral effects, and (3) modeling flaws (Gerarden et al., 2015). The focus of this research is the second category, behavioral affects. Examples of potential barriers to adoption include salience issues, inertia, short-sightedness, heuristic decision-making, prospect theory, and systematically biased beliefs (Gerarden et al., 2015). Unfortunately, not all these factors could be included in the model, but some are present, such as the short-sightedness of consumers. In the model household decision-making is myopic, meaning households demonstrate satisficing behaviour and choose the best option in the current timestep only. There is no way for agents to foresee if possible choices in the future are better than the choices currently presented to them, the information the agents have is imperfect. Meaning the agents are boundedly rational and the utility maximization is myopic.

Besides factors relevant for exploring the attitude-behaviour gap, several components that must be present in the model were identified. Such as a decision theory underpinning the decision-making of households, and a social network to structure the sharing of information between households.

9.2.2. Sub question 2

SQ2: To what extent are these factors captured in the survey data?

The survey data is used to provide specifics on barriers to adoption, technologies, and household characteristics. It is important to see if the identified factors from sub question 1 are represented in the survey data, so that they may be included in the model. The factors identified in sub question 1 cannot be explicitly captured in a survey question, these factors may only show as trends on deeper analysis of the survey data, because consumers are often not aware these barrier and biases affect their decision-making.

The factors relevant to this research could be broadly categorized into three groups:

(1) *Economic factors*, such as the perception of affordability, high upfront cost, and information costs.

(2) *Behavioural factors*, such as bounded rationality, satisficing behaviour, status quo bias (inertia), and loss & risk aversion.

(3) *Social factors*, such as social comparisons, social pressure, imitation, and perception about the attitude of others.

This is not an exhaustive list and is only a selection of the most common barriers present in the literature sample. In the survey data, predominantly group 1 and 3 were represented. Behavioural factors are not directly measured in the survey but are rather emergent from observation of the data.

The survey was carefully designed and featured many questions, but the majority of the survey was not relevant for this research. For instance, the survey features many questions that are relevant for other technologies, not specifically solar PV, and thus were not relevant for this research due to technology specificity.

Additionally, the survey does include questions on the social factors and subjective norms but does not include data on the social network structure of households. This resulted in the social network being structured based on methods and parameters seen in existing literature, weakening the conclusions of the model on social effects and the impact of subjective norms.

Another factor that had limited representation in the survey is the actual behaviour of households, the dependent variable in this research. The survey had already been conducted and is non-longitudinal, meaning that it could not be ensured whether households actually acted on their good intentions of installing solar PV as they indicated in the survey, and if they merely remained intentions or translated into real behaviour. This is a limitation implies that the gap in this research is the attitude-intention gap, rather than the attitude-behaviour gap. Instead of *action* being measured, it is *expected action*.

9.2.3. Sub question 3

SQ3: How can these factors be represented in an agent-based model?

The literature review highlighted the need for a theoretical foundation on which the decision-making of households would be based. Based on the literature review Ajzen's theory of planned behaviour was chosen. TPB structured the conceptualization of the household decision-making, it provided the framework for how the factors could be represented in the model. Operationalizations of TPB have been done before, for this research the (Muelder & Filatova, 2018) operationalization was the best fit as the basis for this model, this operationalization was used as basis and adapted to fit the survey data.

The attitudes and subjective norms of every household agent are dependent on context-dependent factors: financial, environmental, and social. These context-dependent factors contribute to the households' overall utility in a weighted sum, with the heterogenous static weights derived from statistical analysis of the survey data. Initially, groupings of roughly five questions were formed that shaped the utility factors, but this led to several issues: (1) questions are selected subjectively, (2) not all questions showed significant correlation to the intention to invest in solar PV, and (3) the survey questions were all weighed equally while some are more influential than others. To address this issue, binary probit regression was performed to select the single survey question that best represents the specific utility factor.

For factors that were not represented in the survey data, other techniques were applied to allow them to be represented in the model anyway. For instance, during the literature review the necessity of a social network to represent social effects became clear, but due to a lack of data the social network is not empirically grounded with survey data. Instead, the social network is a small-world network constructed with the Watts & Strogatz algorithm, and parameters are based on existing literature. Another example is the supply side, which is heavily stylized considering the focus of the model is on the demand side, specifically consumer behaviour.

9.2.4. Sub question 4

SQ4: To what extent does each identified factor contribute towards shaping the attitude-behaviour gap?

This sub question is addressed with the results from the time-dependent global sensitivity analysis. A set of six input parameters representing various factors were explored. These parameters are psychological factors that play a role in the decision-making of households and contribute towards the system level behaviour. When combined, economic factors (the economic utility and economic uncertainty) contribute towards the emergence of the attitude-behaviour gap to a greater extent than social factors or environmental factors, especially in later stages of the simulation, when the diffusion process has slowed down and has almost reached saturation. Depending on the operationalization of the PBC component, the perception of affordability (represented by the PBC) also demonstrates a significant impact on the emergence of the attitude-behaviour gap.

Other factors identified and discussed in sub question 1 were not present in the global sensitivity analysis, but still play a crucial role in the behaviour of households in the model. In the ABM developed for this research the household agents are boundedly rational and display satisficing behaviour, these factors underpin all the decisions made by the households but are not explicitly represented in the global sensitivity analysis, but are rather behaviour that is endogenous to the decision-making of households in the model.

9.2.5. Sub question 5

SQ5: What are policy interventions that can contribute towards closing the attitude-behaviour gap, and what is their effectiveness?

In this research two policy interventions have been explored, a feed-in tariff referred to as the *salderingsregeling* in The Netherlands, and a tax-rebate referred to as *BTW-aftrek*. Without policy that ensures fair compensation for energy that the households generate (but do not consume themselves) and return to the grid, there is more investment risk and uncertainty involved about future revenue, making it is less economically attractive for households to adopt solar PV due to the lower return on investment. Decreasing the upfront cost of solar PV installations (by offering tax-rebates) decreases the payback period, making solar PV more economically attractive for households, allowing them to recoup their investment quicker.

From the model results the conclusion can be drawn that the Dutch policies are effective in making solar PV more appealing for small-scale users, increasing adoption rates significantly by lowering the economic barriers for households. Even for households that hold positive attitudes towards the environment, the economics remain an important aspect that ultimately determines their behaviour, and by structuring policies that specifically address these economic barriers the attitude-behaviour gap can be shrunk. However, the cost-effectiveness of these policies was not considered in this research, so there exists a trade-off between public spending and environmental benefits. Public money spent on other policy interventions that protect the environment and promote sustainability may be a better option.

Due to the current energy crisis caused by the invasion of Ukraine, the robustness of both policy interventions was analyzed in scenarios with high energy prices. Model results indicate that in scenarios with electricity prices above 0.2 €/kWh the economic benefits for households are so significant that the effects of the *salderingsregeling* are barely noticeable, and the tax rebates are the main determinant of the diffusion rate.

Nevertheless, this does not imply that these two policy interventions, or financial policy interventions in general, are the only effective interventions. The spotlight is often on financial instruments, but information-based policy instruments may aid in improving knowledge or attention to an issue or a technology as well. Consumers may not be aware that their consumption directly affects the environment. Additionally, complete information on the energy-efficient technology and performance of a product aids the consumer in estimating the costs and benefits properly.

9.2.6. Sub question 6

SQ6: How can the results of this study aid policymakers in closing the attitude-behaviour gap?

The results of this research can indicate what factors are important barriers to adoption and how they contribute towards the emergence of the attitude-behaviour gap. These results may eventually lead to policy interventions that can realize petajoules of potential energy savings, by closing the attitude-behaviour gap. Model results indicate that economic barriers to adoption remain a large contributor, and that economic incentives for small-scale consumers such as households are a viable strategy. Due to the data limitations, stylized components of the model, and assumptions the results are not exact, but give a good indication of the system-level behaviour and the biases that inhibit consumers when making choices on energy efficiency.

The ex-ante exploration of the policy interventions shed light on the impact of the proposed phase-out of the *salderingsregeling* (Tweede Kamer der Staten-Generaal, 2020). The proposed phase-out would gradually reduce the amount of electricity households can supply back at full price, from the current 100% to 0% in 2031. However, the return fee is still a point of discussion and minister Jetten for Climate and Energy supports setting the return fee at 80% of the households' electricity price. This is a very relevant topic considering the current discussion around the topic, to consider what the potential effects of phasing out the *salderingsregeling* are on the adoption of solar PV installations. Results from the experiments also illustrated the robustness of the policy interventions under high electricity price scenarios, relevant for the current energy crisis.

10 Reflection & Future Research

In this final chapter the methodology, generalizability of results, and limitations are reviewed. The methodological challenges are presented, and choices made are justified. The choice of theoretical foundation and other methodological challenges and considerations made throughout the simulation study are reviewed. The main takeaway is the strengths and weaknesses of the survey data. While it offered a strong empirical foundation for parametrization of the household agents, it also limited the model somewhat due to the fact the survey had already been conducted, this had implications for various model components and factors.

10.1. Reflection on Research Methodology

This research consisted of a simulation study to simulate the different relevant social and technical components and the emergent behaviour present in the chosen socio-technical system. Sociotechnical systems are inherently complex due to the many components acting in parallel, the evolution over time, downward causation, and the involvement of values, emotions, and norms (Chappin et al., 2019). Therefore, a modelling method that can adequately represent these characteristics is required. Agent-based simulation modelling was the right modelling paradigm for the task. The bottom-up perspective of ABM is ideal for portraying the decision-making of individual households and subsequently exploring the emergent system behaviour, in this case the emergence of the attitude-behaviour gap. Other technical modelling paradigms could likely give better descriptions of the technical aspects of prosumers and the electricity net but will neglect social and behavioural aspects relevant for addressing the main research question. The strength of ABM is the combination of the technical, social, and economic aspects relevant to the problem. The exact methodology used for this research is based on several academic sources that discuss the modelling of energy systems and socio-technical systems (Chappin et al., 2019; Nikolic & Ghorbani, 2011; Van Dam et al., 2013).

In the literature review it became apparent that the household decision-making is generally structured based on decision theories from established psychological research supported by empirical evidence. This method was adopted, and Ajzen's theory of planned behaviour was chosen to structure the decision-making. Since the choice of decision theory is up to the modeller it is hard to argue (without further research) whether this was the correct theory to use, nonetheless TPB was very valuable in structuring the decision-making process of the households. The operationalization of TPB was a methodological challenge because there is no objective method of implementing the theory in a model (Muelder & Filatova, 2018). It is not the scope of this research to compare & contrast different TPB implementations, therefore an implementation based on the publication of Muelder & Filatova (2018) was chosen because it displays lower sensitivity to exogenous architectural parameters compared to the other implementations, and it was designed based on solar PV adoption.

Likewise, the literature review highlighted that generally existing publications use an empirical foundation for model parametrization. Input parameter values from survey data offer a strong empirical foundation and ensures the model is properly calibrated, therefore this methodology was adopted by incorporating existing survey data into the model. While this gave the research a strong empirical foundation, it also limited the research somewhat because the survey had already been conducted. Instead of the traditional approach where participatory stakeholder involvement is used for the system analysis and leads to identifying additional components and empirical evidence necessary to get a complete image of the system, in this research approach the model was built around the existing survey data, as additional data could not be gathered. Additionally, the survey was cross-sectional and not longitudinal, which led to the model validation being performed in a non-traditional manner.

A novel method used in this research is the combinatorial optimization approach for synthetic population generation. Agent behaviour is largely dependent on agent attributes. While attributes can be pulled from generic distributions, this does not guarantee that agents have realistic sets of attributes, take for instance a mismatch between a high-income class and a tiny house surface area. In this research population generation is achieved by sampling a synthetic population based on the individual-level local survey data, and ensuring it matches macro-level marginals of the Dutch population to ensure the generalizability of the results.

The innovation of this research is the combination of the abovementioned methodologies: a theoretical foundation for the household decision-making, an empirical foundation based on survey data, and the combinatorial optimization approach for generalizability of the results. However, it is impossible to conclude whether this provided benefits, due to the limitations of the survey and lack of longitudinal survey data that restricted the model validation.

Despite optimizations and parallelization, computational limitations resulted in the global sensitivity analyses having a relatively low number of samples increasing the 95% confidence intervals. However, one could argue this was due to time constraints more so than due to methodological weaknesses. Nevertheless, future research should employ servers with more computational power to increase the number of samples and decrease the confidence intervals.

10.2. Reflection on Generalizability of Results

In section 8.1 the model validation was performed and discussed. As discussed before, the survey was cross-sectional and not longitudinal, which led to the model validation being constrained. However, the ABM created for this research is an exploratory model, it is meant to support conclusions based on a limited number of experiments, it is not meant for predicting the future. The goal is to create insights into what factors contribute towards the emergence of the attitude-behaviour gap, in this aspect the model was valid, and the aggregate system level conclusions are generalizable.

Another consideration for the generalizability of the results is the origin of the survey data. The survey was conducted in Dalfsen, Overijssel, a relatively rural location outside of the more urban Dutch Randstad. While this is not an issue per se, it would limit the generalizability of the results, people living in Dalfsen may have higher environmental attitudes or more knowledge regarding the environment than the average Dutch person living in an urban area. This was a major reason for using the combinatorial optimization method, to ensure the macro-level statistical measures were as close to the Dutch population as possible, so that the results are generalizable. The results are specific to Dutch households due to the survey data used for agent parametrization, but may show similarities to other European countries.

Due to the reliance on various assumptions throughout the modelling process the model outcomes produced by the experimentation are likely not perfect predictions of the diffusion process, but the conclusions drawn from these experiments can be generalized. Some abstractions had to be made, and extra care has been taken to select reliable data sources wherever available, and only make assumptions as a last case resort. A global sensitivity analysis has been performed in section 7.7 that explores the impact of these assumptions. One of the choices made was to select the energy price of 2021, before the energy crisis due to the invasion of Ukraine, to ensure the model results are more generalizable, as the high energy prices we experience currently are an exception and not the norm. Scenarios with high energy prices have been added to explore situations similar to the current energy crisis in the model.

In this research solar PV is the energy-efficient technology in focus. This so-called *technology specificity* is a key aspect of designing ABMs, because the factors that households consider when choosing to adopt a certain energy-efficient technology is strongly technology dependent (Moglia et al., 2017). The way people make decisions about efficient lighting or solar PV is dependent on the product on offer, and the attributes of the products (Moglia et al., 2017). One could imagine that consumers may prefer certain light qualities such as color or level of illumination for aesthetics, while this is not relevant for solar PV at all. This means the TPB operationalization and model results are specific to solar PV and will likely not be generalizable to the diffusion of other technologies. Solar PV is characterized by the high upfront cost and economic barriers to adoption will therefore be emphasized.

In conclusion, the results of the model may not be generalizable directly—despite steps taken to ensure the contrary—but the insights into the system level behaviour and emergence of the attitude behaviour gap are generalizable under certain circumstances. Future research with longitudinal survey data could refine the model to be more widely applicable.

10.3. Scientific Relevance

Modelling efforts have been made with varying degrees of rigour and success. The attitude-behaviour gap has been studied, but aside from a list of potential explanations it is not clear exactly how it is shaped and to what extent factors contribute towards emergence of the gap. This research managed to quantify the contribution of various factors toward the emergence of the attitude-behaviour gap. Besides this main contribution, the contributions of this research are multifold:

Firstly, an empirically grounded ABM has been developed to analyze solar PV diffusion and emergence of the attitude-behaviour gap in a heterogenous population of households in The Netherlands. The ABM was developed with user friendliness and customization in mind, values are expressed by parameters that may be changed easily by the user. Additionally, a description was given of the system and model in fine detail in terms of technological, social, behavioural, economic, and environmental aspects at a low system level. The model could be improved by adding components or by using more encompassing survey data.

Secondly, a more appropriate household initialization method of *combinatorial optimization* based on individual-level survey data has been employed to ensure the generalizability of the results to Dutch households.

Additionally, due to lack of household social network analysis in the survey data, other methods used in similar literature were used instead. A small-world network refined with agent attributes such as income class, education, and age has been implemented. The network is refined with these agent attributes because respondents noted that they generally share information with each other based on similarities in these attributes (see section 5.4).

The combination of these techniques is novel in the energy consumption domain and is especially valuable considering the main research question. The personal attributes of households have been shown to be significant indicators of energy consumption behaviour in existing research.

10.4. Societal Relevance

As discussed in the introduction chapter, the energy transition requires everyone to contribute if we are to reach the long-term goals stipulated in the Paris climate agreement in time. The responsibility does not rest solely on the shoulders of policymakers and energy producers. On the demand side the consumer plays an important role in the energy transition with their energy consumption behavior and sustainable consumption in general. Limiting climate change is imperative, but when tasked to make behavioral changes convenience and cost remain predominant for consumers. Even if it is in the best interest of the consumer to invest in energy-efficient technologies (both financially and regarding the environment) investment does not occur, and energy-efficient technologies remain underutilized. The asymmetry between consumer attitude towards sustainability and their actual energy consumption behaviour remains an understudied issue.

This research explored this asymmetry, referred to as the attitude-behaviour gap. With the use of an ABM simulation the emergence of the attitude-behaviour gap was explored, to study what factors, and to what extent these factors contribute to emergence of the gap. It can be concluded that economic barriers contribute towards the emergence of the attitude-behaviour gap to a greater extent than social effects, or environmental attitude. These results, in addition to the ex-ante policy intervention exploration for evaluating policy impacts to judge their impact on the adoption rate of household solar PV, may help consumers in making sustainable decisions with regards to investing in energy-efficient technologies and energy consumption behaviour in general, and may help policymakers with designing policy interventions that focus on reducing the predominant barriers to adoption. Hopefully consumers see the importance of research efforts like these, and the value of sharing their data with researchers.

10.5. Limitations & Future Research

This section will discuss the limitations that are introduced by some critical assumptions, and general limitations of this research. To understand the context of the model it is important to be aware of all the assumptions, a full list of model parameters, their source, and assumptions can be found in Appendix D. A global sensitivity analysis that explores the impact of these assumptions on the robustness of the conclusions has been performed in section 7.7. This research and its limitations revealed many opportunities for future research. The assumptions were generally made due to time constraints and data limitations, these are the two foremost issues that would improve this simulation study and could be resolved with additional research and survey data.

10.5.1. Households

Firstly, the limitations with regard to households. The households are of the same composition and do not evolve over time, and electricity consumption of households is static. This means phenomena such as the rebound effect—where improvements in efficiency lead to cost reductions allowing consumers to buy and use more of the product in return—could not be observed in the model. Better integration with data on household electricity consumption could improve the model.

Secondly, there is homogeneity in the solar PV installations. All installations share similar technological characteristics, such as peak wattage and lifetime. Households do not have a choice of PV installation, while in reality the choice of PV installation can be a quite complex decision problem for consumers, with many relevant aspects (size, cost, provider, maintenance, wait time, insurance, etc.) and may introduce information costs. The information costs may pose an additional barrier to adoption for households and should therefore be explored in future research.

Thirdly, the economic limitations of the model. Despite the importance of economic factors for the diffusion process, simplifications had to be made due to time constraints. Electricity price is fixed, it is based on historical prices and does not evolve over time. Households are not able to choose or change energy providers, every household pays the same price for electricity. Discount rates are also fixed and based on historical data; they do not evolve over time. Better integration with historical data improves the accuracy of the model.

10.5.2. Social Network

The social network is assumed to be static, no relationships are formed or broken throughout the simulation. Based on the survey data the connections between households are weighted based on age, income, and education parity, an abstraction of reality. A small-world network created with the Watts-Strogatz algorithm is used to represent the information that can flow between households, as this type of network is commonly used in similar research. This is generally considered a good approximation for a social network, but it is not clear whether this is the best approach for establishing the social network. Ideally the social network characteristics could be established on empirical survey data, but this type of data is hard and expensive to gather and therefore often not accessible. Network parameters have been investigated in the global sensitivity analysis and the number of connections (model parameter *WS_K*) has an influence on the model results, therefore the uncertainty of the social network is a limitation of the model as mentioned in the conclusion to the main research question. While it is generally expensive, a social network analysis survey of households could improve the strength of the conclusions on subjective norms.

10.5.3. Combinatorial Optimization

While this research employed the combinatorial optimization method for synthetic population generation, the benefits could not be quantified. Further research could apply this method to another existing model (with longitudinal survey and validation data), to explicitly quantify the benefits to the generalizability of results of this method.

10.5.4. TPB

The operationalization of some TPB components led to limitations, discussed in the next sections. The theoretical foundation in general leaves room for future research. The qualitative social science theory is chosen by the modeller, and the implementation and operationalization are rather subjective. Efforts have been made to investigate the impact of these methodological issues (Muelder & Filatova, 2018) and should be continued to hopefully standardize the implementation of qualitative theories.

The perceived behavioural control component of TPB may include financial, knowledge, and time constraints. However, as the perception of affordability is often the most significant barrier to adoption (Rai & Beck, 2015; Rai & Robinson, 2015) only the financial aspect is included in the PBC component. Future research could expand the PBC component in the model to cover more constraints besides financial, it could be expanded with knowledge constraints and time constraints, to capture internal (determination, own ability) in addition to the existing external (resources, affordability) self-efficacy. Additionally, in the threshold operationalization of PBC it is not quite clear what the threshold value should be, and what it should be based on (Muelder & Filatova, 2018), therefore it is user defined.

In this research PBC directly influences the behaviour because the 'actual behavioural control' component is omitted from the operationalization. Jackson (2005) agrees that if the individual's perceptions are not misguided the PBC is likely to indicate actual behavioural control. If a person has the willpower over their own actions then intention is likely closely related to behaviour (Jackson, 2005), but this has not been empirically verified.

The main research question considers the attitude-behaviour gap, this implies the dependent variable is behaviour, yet the survey data only measures self-reported intention. Due to the non-longitudinal survey data, it could not be observed whether households actually acted on their good intentions of installing solar PV as they reported in the survey, if they merely remained intentions or translated into observed behaviour. This limitation implies that the gap in this research is the attitude-intention gap, rather than the attitude-behaviour gap. Instead of *action* being measured, it is *expected action*. This means within the model results and conclusions there likely is a discrepancy between the self-reported intention and the observed behaviour. Future research should include longitudinal survey data with observed behaviour to avoid this limitation.

10.5.5. Policy Interventions

Two policy interventions focused on households were explored in this research, a feed-in tariff and tax-rebates. This does not imply that these two policy interventions, or financial policy interventions in general, are the only effective interventions. Information-based policy instruments and regulatory instruments could not be explored due to time constraints. In other words, policy interventions were considered in this study, but to a limited extent. Only two policy interventions are explored, and both are financial instruments. Future research could simulate the impact of regulatory approaches or informative & voluntary schemes, or combinations of policy interventions. Along with policy interventions focused on more complicated solutions, such as tradeable certificates or tenders. Additionally, the cost-effectiveness of these interventions should be considered, to explore whether public money spent on other policy interventions that protect the environment and promote sustainability may be a better option.

10.5.6. Conclusion

In conclusion, the abovementioned limitations were commonly introduced due to modelling choices that had to be made due to time constraints and lack of data. Indeed, data availability was the main limitation of this research. As mentioned in the reflection on the research methodology the survey offered a strong empirical foundation, but it also limited the research somewhat because the survey had already been conducted and the survey was not longitudinal. In this research approach the ABM was built around the existing survey data (which was often limited or focused on other energy-efficient technologies) as additional data could not be gathered. However, the benefits of a strong empirical foundation outweighed the limitations imposed by the survey data. Additionally, this model could be applied with different survey data to study the emergence of the attitude-behaviour gap in other populations than the Dutch population which was the focus of this research.

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Appendix A – Final Literature Sample

Table 11
Synthesis table displaying the remaining 11 publications included in the final sample, sorted alphabetically.

Reference	**Title**	**Technology**	**Diffusion vs. Usage**	**Case**	**Theory**
Afman et al., 2013	Agent-Based Model of Transitions in Consumer Lighting	Efficient lighting	Diffusion		Social Networks
Alyousef et al., 2017	Analysis and model-based predictions of solar PV and battery adoption in Germany: an agent-based approach	PV, Battery	Diffusion	Germany	Affect Control Theory (ACT)
Bellekom et al., 2016	Prosumption and the distribution and supply of electricity	PV, Battery	Usage	Netherlands	None
Claudy et al., 2013	Understanding the Attitude-Behavior Gap for Renewable Energy Systems Using Behavioral Reasoning Theory	PV	Diffusion	Ireland	Behavioural Reasoning Theory (BRT)
Eppstein et al., 2011	An agent-based model to study market penetration of plug-in hybrid electric vehicles	EV	Diffusion	US	Social Networks
Jensen et al., 2016	Energy-efficiency impacts of an air-quality feedback device in residential buildings: An agent-based modeling assessment	Ventilation	Diffusion	Germany	Theory of Planned Behaviour (TPB)
Kowalska-Pyzalska et al., 2014	Turning green: Agent-based modeling of the adoption of dynamic electricity tariffs	Dynamic tariffs	Usage	-	Theory of Planned Behaviour (TPB), Value belief norm (VBN)
Noori & Tatari, 2016	Development of an agent-based model for regional market penetration projections of electric vehicles in the United States	EV	Diffusion	US	Utility function
Rai & Robinson, 2015	Agent-based modeling of energy technology adoption: Empirical integration of social, behavioral, economic, and environmental factors	PV	Diffusion	Austin	Theory of Planned Behaviour (TPB)
Sopha et al., 2011	Exploring policy options for a transition to sustainable heating system diffusion using an agent-based simulation	Heating	Diffusion	Norway	Theory of Planned Behaviour (TPB)
Stavrakas et al., 2019	An agent-based model to simulate technology adoption quantifying behavioural uncertainty of consumers	PV	Diffusion	Greece	Social Networks

Appendix B – Sub Question Discussion

SQ1: What factors are relevant in exploring emergence of the attitude-behaviour gap?

The goal of the first sub question is to get a better understanding of the decision-making process and the attitude-behaviour gap in general, to get a full view of the whole system. This is the starting point of the research approach. Predominantly achieved through desk research and the literature review presented in the previous chapter. By analyzing a wide sample of literature, the relevant concepts can be identified to get a better understanding of the system to be modelled. The scope of the literature review is intentionally broad to capture a wide variety of factors that are relevant to human decision-making behaviour and the emergence of the attitude-behaviour gap, to ultimately identify overarching themes or commonly investigated factors in the literature that are essential components in the socio-technical system.

By explicitly formulating the problem in the problem formulation step and by deciding the intended model usage, one gives direction to the research and sets the scope and boundaries of the model. Deciding these matters early on it aids in the model conceptualization process. Besides identifying the relevant actors and their behaviour, the goal is to identify the internal structure of these components to allow further analysis (Nikolic & Ghorbani, 2011).

SQ2: To what extent are these factors captured in the survey data?

This sub question is added to address the fact that the survey was conducted before the research itself. The system identification step is normally an inherently social process (Nikolic & Ghorbani, 2011) with participatory stakeholder involvement. The survey data is used to provide specifics on barriers to adoption, technologies, and household characteristics.

However, the survey that offers the empirical foundation for the simulation model has already been conducted, this limits the modelling process to some extent. Instead of the traditional approach where participatory stakeholder involvement is used for the system analysis and leads to identifying additional components and empirical evidence necessary to get a complete image of the system, in this research the model must be built around the existing survey data. Therefore, it is important to see if the identified factors from sub question 1 are represented in the survey data, and if they are not represented if they can be based on other empirical data such as national macro-level data published by CBS. While promising, multi-modelling (multi-paradigm) approaches are not considered due to time constraints, therefore some variables must be considered exogenous instead.

Additional data processing must occur to derive the weights from the survey, that used in the TPB utility functions in the operationalized model. The survey also features a section on ‘social network and interactions’ which may aid in structuring the social network if the data is appropriate. Data processing and data analysis is done in SPSS.

The first two sub questions lay the foundation based on the body of knowledge and guide the process that leads to the conceptual framework of the system.

SQ3: How can these factors be represented in an agent-based model?

While the previous steps the goal was to get a better understanding of the system to be modelled, in this phase the model is considered in terms of model formalization and software implementation (Nikolic & Ghorbani, 2011). The factors identified under sub question 1 must be formalized in order to implement them in an ABM.

Important choices on the level of detail for certain components of the system are made here. These choices are also based on the demarcation and model scope decided in sub question 1. Since the model is implemented based on the problem formulation the focus and level of detail on a specific component may be more, or less, than others. For instance, the supply side of the electricity market is stylized heavily considering the focus of the model is on the demand side, specifically consumer behaviour.

Similar important choices must be made for the experimental design. Considering the main research question, what are relevant experiments to run and variables to measure? Additional experimental options such as run length, number of repetitions, scenario design, and parameter sweeps will be considered (Nikolic & Ghorbani, 2011). This step signals the beginning of the iterative model building process, which is done in NetLogo.

SQ4: To what extent does each identified factor contribute towards shaping the attitude-behaviour gap?

As emphasized in the previous sub question the modelling cycle is an iterative process, software implementation and model evaluation are a continuous process. Verification must occur to check whether the translation from conceptual model to computational model has been executed appropriately. Furthermore, validation must be performed, traditionally this is done by comparing model outcomes to observed reality. However, in this ex-ante exploratory research there exists no feasible method of collecting observed reality data, meaning validation is impossible in the traditional sense (Nikolic & Ghorbani, 2011). This means other methods of validation must be performed, such as qualitative and quantitative validation based on the survey data.

Once verification and validation have occurred the model has been established it can be used to simulate a base case scenario without any policy interventions to analyze the relationship between the factors and the emergence of the attitude-behaviour gap, to be used in comparison with policy scenarios in the next sub question. Since NetLogo is fairly limited in terms of data analysis and data visualization, the Pandas library for Python is used.

SQ5: What are policy interventions that can contribute towards closing the attitude-behaviour gap, and what is their effectiveness?

While it is interesting how the factors contribute towards the attitude-behaviour gap in itself, it is more useful to explore policy interventions that may aid in closing the gap. Policy scenarios where the effects of different policy interventions, or a mix of policy interventions, can be explored are required to address this sub question. A wide variety of policy instruments is used in the scenarios ranging from financial and market-based instruments to regulatory approaches and information instruments. The aim is to explore what policy interventions (and their method of implementation) are effective in raising the rate of diffusion of solar PV, and in reducing energy consumption and GHG emissions. The model outcomes may conflict or agree with established views, and it is useful to see why this is the case.

SQ6: How can the results of this study aid policymakers in closing the attitude-behaviour gap?

This sub question signals the end of the modelling process. First, the limitations and assumptions in the model must be properly addressed and communicated to policymakers. Then the recommendations supported by the model outcomes can be shared. Advice will mainly consist of two sections, one that presents the factors that play a role in the emergence of the attitude-behaviour gap, and another section that lists promising policy interventions with their benefits and limitations. Besides recommendations to policymakers, consumers may also be interested in what they can change personally and can receive simple recommendations focused on behaviour. Lastly, future research options and other possible applications of the model are presented.

Appendix C – TPB Factors & Survey Questions

The tables below display the original groupings of the survey questions that constituted the utility factor in question. This idea was abandoned and eventually a single survey question was chosen to represent the specific utility factors (refer to section 5.3.3), this single question is highlighted in the tables.

Table 12
Questions contributing to the environmental utility factor.

Environmental Factor		
Label/ Question	**SPSS variable name**	**Inverse?**
Climate change is caused by a hole in the earth's atmosphere.	Q100_1	
Climate change issues should be dealt with primarily by future generations.	Q100_7	yes
The effect of environmental issues on human health is worse than we realize.	Q70_2	
Environmental issues, even in one region, affect other regions.	Q70_1	
Environmental impacts are frequently overstated.	Q70_3	yes
Environmental issues like climate change are caused by our use of fossil fuels.	Q70_4	
Protecting the environment is a means of stimulating economic growth.	Q70_5	
Nature is fragile and if we don't take care of it properly, it could destabilize.	Q70_9	
I believe that my energy source choice (renewables or fossil fuels) has an impact on the environment.	Q70_6	
I think avoiding fossil fuels use will help solve wider environmental issues	Q100_6	

Table 13
Questions contributing to the social utility factor.

Social Factor	
Label/ Question	**SPSS variable name**
I would reduce my energy consumption if more practical information on how to reduce energy consumption at home.	Q540_1
I would reduce my energy consumption if more practical information on how I can invest in green energies (e.g. install solar panels) would be available.	Q540_3
I would reduce my energy consumption if finding out that my households uses more energy than similar households.	Q540_4
I would reduce my energy consumption if public labels which neighbors can see would exist.	Q540_6
Encouragement or actions of friends and family.	Q540_7
Encouragement or actions of group/associations that I am part of them.	Q540_8
Governmental policies and subsidies (i.e. municipalities, provincial, national level).	Q540_10

Table 14
Questions contributing to the economic utility factor.

Economic Factor	
Label/ Question	**SPSS variable name**
In your view, how serious are the following issues facing the world today? Economic concerns (e.g. unemployment, inflation, financial crisis)	Q50_1
Protecting the environment is a means of stimulating economic growth	Q70_5
If I had more money, I would pay more to use only renewable energy	Q450_1
If there were subsidies, I would produce part of my green energy consumption (e.g. install solar panel or fund a wind turbine)	Q450_2
I took the energy costs into account when purchasing or renting my current residence	Q450_3
How likely would you reduce your energy consumption under the following conditions? if energy prices would be higher	Q540_2
How likely would you reduce your energy consumption under the following conditions? if it would be less expensive to invest in energy-efficient equipment	Q540_5

Appendix D – Model Parametrization & Assumptions

D.1. Model Parametrization

The table below present an overview of the global variables present in the models. The parameter, its value, and the source are shown.

Table 15
Exogenous global variables that are parametrized at model initialization.

Global Scope			
Parameter	**Value**	**Source**	**Comment**
CO_seed	random	User defined	
run_seed	random	User Defined	
time_horizon	40	User defined	
income_class	heterogenous	User defined	
income_class_average	2.89	Survey	
initial_pv_percentage	0.20	(CBS, 2022c, 2022d)	
interest_rate	0.015	(De Nederlandsche Bank, 2022)	Changed from negative at the beginning of the year to roughly 1.5% currently.
weight_distribution	heterogenous	User defined	
weight_eco weight_env weight_soc	Varying	User defined	
WS_K	4	(Stavrakas et al., 2019)	
WS_Beta	0.1	(Maya Sopha et al., 2011)	
n_households	1000	User defined	
household_consumption _factor	0.75	Assumption	Households assumed to consume ¾ of the energy they generate.
pv_cost_per_kwp	1450 €/kWp	(Milieu Centraal, 2021)	Includes BTW-tax, installation, and transformer.
pv_peak_power	220 Wp/m²	(Milieu Centraal, 2021)	
pv_performance_ratio	0.80	Assumption	
pv_lifetime	25 years	(Jordan et al., 2016)	
electricity_cost	0.134 €/kWh	(CBS, 2022a)	
pv_SDE_premium			
pv_irradiation_factor	0.92 kWh/Wp	(SolarCare, 2021)	Long term yearly average between 2012-2020.

pv_avoided_cost_per_kwh	0.134 €/kWh	(CBS, 2022a)	Assumed to be equal to electricity cost.
pv_co2_per_kwh	0.42 kg/kWh	(CBS, 2020b)	Underestimation because transport is not considered.
pv_avg_co2	0.676 Ktonne/kWh	(CBS, 2009)	
expval_gender	1.49	(CBS, 2021c)	Expected values (marginals) from the Dutch population for CO procedure
expval_age	42.3	(CBS, 2021c)	
expval_income_class	3.2	(CBS, 2021b)	
expval_education	3.18	(CBS, 2021a)	
expval_energylabel	4.12	(CBS, 2011)	
expval_houseage	4.73	(CBS, 2022c)	
expval_size	3.40	(CBS, 2022c)	
PBC	probablistic	User Defined	
PBC_threshold	0.5	User Defined	

Table 16
Exogenous agent variables that are parametrized at model initialization.

Agent Scope			
Parameter	**Value**	**Source**	**Comment**
hh_*	Varying	Survey	Personal attributes and dwelling attributes.
surface_area	Varying	Survey	Interpolated from house size class.
roof_area	Varying	Assumption	Half of house surface area.
w_eco w_env w_soc	Varying	Survey	Heterogenous weights.

Table 17
Edge weights for the social network.

Link Scope			
Parameter	**Value**	**Source**	**Comment**
weight	Varying	Survey	Determined based on weighted sum of age, education, and income class parity

D.2. Policy Intervention Parametrization

The model includes variables that represent policy interventions, these parameters are shown below. Refer to section 6.5. for an in-depth discussion.

Table 18

Exogenous policy intervention global variables that are parametrized at model initialization.

Parameter	Value	Source
saldering	Off constant phase-out phase-out 80% lower bound	(Tweede Kamer der Staten-Generaal, 2020)
pv_saldering	[1 – 0] [a]	(Tweede Kamer der Staten-Generaal, 2020)
saldering_return_fee	0.09 €/kWh	(Milieu Centraal, 2022)
tax_rebate	Off 21% BTW 10%	(Rijksoverheid, 2022)

[a]Gradual phase-out from 1 to 0 as displayed in table 1.

D.3. Model Assumptions

Households

- Households are of the same composition.
- *House surface area* is interpolated from the ordinal variable *surface area class.* With a lower bound of 12m.
- Roof size is assumed to be half of the total surface area of the house. In line with 2 story buildings seen in Dalfsen, Overijssel.
- Every household has a roof configuration that allows for solar PV installation.
- Households do not have future information.
- The initial share of households that starts with solar PV already installed is selected randomly.

Technology & Energy

- Solar PV installations are all 220Wp/m^2 based on the most commonly installed solar peak wattage.
- Solar PV installations are homogenous (except in size):
    - Cover the entire roof area
    - Angled at 35 degrees, pointed in the south direction
    - Total output based on average Dutch solar irradiation factor from 2012-2020 of 0.92 kWh/Wp
    - Lifetime is 25 years

    - Have a clear view of the sky (excluding clouds and other weather)
- Solar PV installations do not decrease in efficiency over time, and do not collect dirt.
- Households assumed to consume ¾ of the energy they generate.
- Adoption of solar PV is considered uni-directional. Households can install solar PV, but may not dis-adopt.

Social Network

- The social network and agent age are assumed to be static. While in reality our social network is dynamic and always evolving, the modelled social network is static; no relationships are formed or broken.
- Connections between households are weighted based on age, income, and education parity.

Economics

- Electricity price is fixed.
- Consumers don't choose energy providers, they all pay the same price.
- Solar PV installation price is constant.
- Interest rate is static.

Appendix E – Model Results

E.1. Simulation Experiment Results

Table 19
Results of all simulation experiments, shown as mean (standard deviation) over 100 repetitions of the last timestep (year 40).

Experi-ment	Parameter	Value	Diffusion rate	Energy Produced	CO2-emissions Prevented	Cost Saved
E0	-	-	-	-	-	-
E1	PBC_factor w_env_scaling w_eco_scaling w_soc_scaling tpb_eco_unc_mean tpb_eco_unc_stddev	[-1, 1] [-3, 3] [-3, 3] [-3, 3] [0, 1] [0, 0.2]	-	-	-	-
E2	salderingsregeling, tax_rebate	off off	0.277(0.026)	2.659(0.250)	1.117(0.105)	-0.719(0.067)
E3	salderingsregeling, tax_rebate	current 21%	0.751(0.045)	7.184(0.431)	3.017(0.181)	4.430(0.265)
E4a E4b E4c	salderingsregeling	phase-out phase-out 80% off	0.521(0.043) 0.847(0.033) 0.339(0.038)	4.991(0.419) 8.095(0.329) 3.251(0.37)	2.096(0.176) 3.400(0.138) 1.365(0.155)	1.666(0.140) 5.884(0.239) 0.466(0.053)
E5a E5b	tax_rebate	10% off	0.535(0.046) 0.361(0.033)	5.134(0.448) 3.471(0.312)	2.156(0.188) 1.458(0.131)	2.154(0.188) 0.704(0.063)
E6a E6b E6c E6d E6e	electricity_price	0.2 0.3 0.4 0.5 0.6	0.984(0.007) 0.996(0.002) 0.998(0.001) 0.999(0.001) 0.999(0.001)	9.439(0.070) 9.548(0.039) 9.559(0.041) 9.564(0.036) 9.569(0.033)	3.965(0.029) 4.010(0.016) 4.015(0.017) 4.017(0.015) 4.019(0.014)	15.647(0.116) 30.886(0.126) 45.999(0.197) 61.108(0.229) 76.232(0.266)
E6f E6g E6h E6i	salderingsregeling, tax_rebate	current, 21% phase-out, 21% current, off phase-out, off	0.990(0.004) 0.990(0.004) 0.955(0.012) 0.948(0.014)	9.474(0.055) 9.483(0.052) 9.147(0.125) 9.075(0.151)	3.979(0.023) 3.983(0.022) 3.842(0.053) 3.812(0.063)	15.704(0.091) 13.927(0.076) 11.378(0.156) 9.574(0.159)

E.2. Global Sensitivity Analysis Results

Table 20
Global sensitivity analysis (GSA) result table, 256 runs of 12 parameters. ST represents the total Sobol indices, and S1 the first-order Sobol indices. The 95% confidence intervals are shown in ST_conf and S1_conf.

Parameter	ST	ST_conf	S1	S1_conf
surface_to_roof_area_ratio	0.008478	0.003599	0.002216	0.014382
electricity_cost	0.348838	0.082399	0.257632	0.094206
household_consumption_factor	0.4051	0.110762	0.185222	0.115302
interest_rate	0.077207	0.023597	0.024756	0.050268
WS_K	0.047504	0.014201	-0.00229	0.036347
WS_Beta	0.084932	0.02682	0.023705	0.043356
pv_irradiation_factor	0.146276	0.047829	0.039845	0.071614
pv_cost_per_kwp	0.048944	0.020696	0.017835	0.033188
pv_peak_power	0.006138	0.001712	0.006359	0.01265
pv_performance_ratio	0.134734	0.051505	0.096248	0.057749
pv_lifetime	0.186061	0.060647	0.117118	0.059469
pv_co2_per_kwh	0.007496	0.002784	-0.00087	0.010588
pv_co2_per_kwh	0.007496	0.002784	-0.00087	0.010588

E.3. Time-Sensitive Global Sensitivity Analysis Results

Table 21
Time-dependent global sensitivity analysis result table, 512 runs of 6 parameters. ST represents the total Sobol indices, and S1 the first-order Sobol indices. The 95% confidence intervals are shown in ST_conf and S1_conf. PBC threshold setting is set to probabilistic.

Parameter	ST	ST_conf	S1	S1_conf
PBC_factor	0.003061	0.000747	0.011292	0.006687
w_env_scaling	0.292819	0.075962	0.11825	0.056587
w_eco_scaling	0.349821	0.079388	0.059275	0.066963
w_soc_scaling	0.591561	0.107281	0.332545	0.101833
tpb_eco_unc_mean	0.428901	0.081473	0.18297	0.079759
tpb_eco_unc_stddev	0.011224	0.003948	0.001509	0.011479

Table 22

Time-dependent global sensitivity analysis result table, 512 runs of 6 parameters. ST represents the total Sobol indices, and S1 the first-order Sobol indices. The 95% confidence intervals are shown in ST_conf and S1_conf. PBC threshold setting is set to threshold.

Parameter	**ST**	**ST_conf**	**S1**	**S1_conf**
PBC_factor	0.458503	0.109554	0.250502	0.119414
w_env_scaling	0.210571	0.089913	0.043887	0.029842
w_eco_scaling	0.263623	0.084627	0.013167	0.025156
w_soc_scaling	0.486146	0.122317	0.231053	0.08449
tpb_eco_unc_mean	0.36289	0.106649	0.086557	0.053906
tpb_eco_unc_stddev	0.011457	0.004153	0.00524	0.009698