Dissertation

Decision-making of homeowners regarding building retrofit: empirical and model-based investigations

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Ardak Akhatova, MSc

Supervisor:

Univ. Prof. Dipl.-Ing. Dr. Reinhard Haas
Technische Universität Wien (TU Wien)

Reviewer and Examiner:

Prof. Dr. Valentin Bertsch
Ruhr-Universität Bochum (RUB)

Prof. Dr. Emile J. L. Chappin
Technische Universiteit Delft (TU Delft)

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Abstract

Building retrofits are a critical means of reducing energy demand for space heating, yet adoption rates remain low. To address this challenge, it is essential to both understand the factors that influence homeowners' decisions and model these decision-making processes to evaluate the impact of potential policy interventions. This thesis adopts a dual approach: it first explores the drivers of retrofit adoption through empirical analysis, and then investigates how agent-based modeling (ABM) can be used to simulate and understand these decisions in the context of urban energy transitions.

The first research question focuses on understanding homeowner decision-making about retrofitting. Through principal component analysis (PCA) of a Dutch homeowner survey, the research identifies the key factors associated with energy-efficient retrofit decisions. The analysis shows that older and smaller households with long home tenure are less likely to adopt energy-efficient measures. In contrast, households with high levels of neighborhood involvement are more inclined to adopt solar panels and insulation, likely driven by social trust and influence.

In parallel, the second research question examines how ABM can be used to model decision-making processes in energy-efficient retrofitting. Despite its growing use in various fields, the application of ABM in the context of retrofitting is not yet widespread, highlighting a gap in the existing literature. This research reviews how ABM has been applied in previous studies, identifying the key factors integrated into these models and analysing how agent interactions affect the adoption of energy-efficient measures.

The third part of the thesis builds on this foundation by applying ABM to simulate the impact of homeowner decision-making on broader outcomes

such as neighborhood energy demand. By modeling both techno-economic and socio-psychological decision-making processes, this research shows how different assumptions lead to varying outcomes in terms of retrofit adoption and energy savings, providing valuable insights for policymakers. While subsidies can significantly boost heat pump and insulation adoption in the techno-economic model, they prove less effective in the socio-psychological model, where behavioral barriers like low perceived control and attitudes toward heat pumps hinder uptake. In such cases, stronger regulatory measures, such as a ban on gas boilers, may be more successful in driving sustainable heat transitions.

Together, this thesis covers both the factors that drive energy-efficient retrofitting and the potential of ABM as a tool for simulating policy interventions. It stresses the need for integrated policies that consider both techno-economic and socio-psychological drivers of retrofitting adoption. Future research could build on this work by exploring additional technologies, such as hybrid heat pumps, and by integrating more granular, contextualised data into ABM simulations for even more accurate policy guidance.

Kurzfassung

Gebäudesanierungen sind entscheidend zur Reduktion des Energiebedarfs von Gebäuden. Dennoch bleiben die Umsetzungsraten gering. Um diese Herausforderung zu bewältigen, ist es wichtig, sowohl die Faktoren zu verstehen, die die Entscheidungen von HausbesitzerInnen beeinflussen, als auch diese Entscheidungsprozesse zu modellieren, um die Auswirkungen potenzieller politischer Interventionen zu bewerten. Diese Dissertation verfolgt einen doppelten Ansatz: Zunächst werden die Treiber für die Umsetzung von Sanierungsmaßnahmen durch eine empirische Analyse untersucht. Anschließend wird erforscht, wie die agentenbasierte Modellierung (ABM) genutzt werden kann, um diese Entscheidungen im Kontext der urbanen Energiewende zu simulieren und zu verstehen.

Die erste Forschungsfrage konzentriert sich auf das Verständnis der Entscheidungsfindung von HausbesitzerInnen in Bezug auf Sanierungen. Mit Hilfe einer Principal-Component-Analysis (PCA), die auf die Ergebnisse einer niederländischen Umfrage unter HausbesitzerInnen angewandt wurde, werden die Schlüsselfaktoren identifiziert, die mit der Entscheidung zur energieeffizienten Sanierung verbunden sind. Die Analyse zeigt, dass ältere und kleinere Haushalte mit langer bisheriger Wohndauer im Gebäude weniger wahrscheinlich energieeffiziente Maßnahmen umsetzen. Im Gegensatz dazu neigen Haushalte mit hoher Nachbarschaftsbeteiligung eher dazu, Solaranlagen und Dämmungen umzusetzen, was auf höheren sozialen Zusammenhalt zurückzuführen ist. Parallel dazu untersucht die zweite Forschungsfrage, wie ABM genutzt werden kann, um Entscheidungsprozesse bei energieeffizienten Sanierungen zu modellieren. Trotz ihrer zunehmenden Anwendung in verschiedenen Bereichen ist der Einsatz von ABM im Kontext von Sanierungen noch nicht weit verbreitet, was eine Lücke in der bestehenden Literatur aufzeigt. Dieser Teil der Arbeit untersucht, wie ABM in früheren Studien

angewendet wurde, und identifiziert die Schlüsselfaktoren, die in diese Modelle integriert wurden, sowie die Auswirkungen von Interaktionen zwischen AgentInnen auf die Umsetzung energieeffizienter Maßnahmen.

Der dritte Teil der Dissertation baut auf diesem Fundament auf, indem ABM verwendet wird, um die Auswirkungen der Entscheidungen von HausbesitzerInnen auf den Energiebedarf sowie Energieträger-Mix in der Nachbarschaft zu simulieren. Durch die Modellierung sowohl techno-ökonomischer als auch sozialpsychologischer Entscheidungsprozesse zeigen die Ergebnisse, wie unterschiedliche Annahmen zu verschiedenen Ergebnissen in Bezug auf die Sanierungsumsetzung und Energieeinsparungen führen. Während Subventionen die Umsetzung von Wärmepumpen und Dämmungen im techno-ökonomischen Modell erheblich steigern können, erweisen sie sich im sozialpsychologischen Modell als weniger wirksam, da verhaltensbedingte Hürden und Einstellungen gegenüber Wärmepumpen die Umsetzung behindern. In solchen Fällen könnten stärkere regulatorische Maßnahmen, wie ein Verbot von Gasheizungen, erfolgreicher sein, um die Energiewende im Gebäudesektor voranzutreiben.

Diese Dissertation untersucht sowohl die Faktoren, die energieeffiziente Sanierungen antreiben, als auch das Potenzial von ABM als Werkzeug zur Simulation politischer Interventionen. Sie betont die Notwendigkeit integrierter politischer Maßnahmen, die sowohl techno-ökonomische als auch sozialpsychologische Treiber der Sanierungsumsetzung berücksichtigen. Zukünftige Forschungen könnten auf dieser Arbeit aufbauen, indem zusätzliche Technologien wie Hybrid-Wärmepumpen untersucht und granularere, kontextualisierte Daten in ABM-Simulationen integriert werden, um noch genauere politische Empfehlungen abzuleiten.

Contents

Abbreviations

ABM	Agent-Based Model
ABS	Agent-Based Simulation
BSM	Building Stock Models
CHP	Combined Heat and Power
DH	District Heating
EEP	Energy Efficiency Program
EER	Energy-Efficient Retrofit
EEW	Energy-Efficient Window
EC	Energy Champion
EPBD	Energy Performance of Buildings Directive
EPC	Energy Performance Certificate
EU	European Union
EV	Electric Vehicle
GB	Gas Boiler
GHG	Greenhouse Gas
HP	Heat Pump
HVAC	Heating, Ventilation, and Air Conditioning
IEA	International Energy Agency
INS	Insulation (thermal)
IPCC	Intergovernmental Panel on Climate Change
MAS	Multi-Agent Systems
MEPS	Minimum Efficiency Performance Standard
NPV	Net Present Value

ODD	Overview, Design Concepts and Details
ODD+D	Overview, Design Concepts and Details + Decision-making
OOP	Object-Oriented Programming
PC	Principal Component
PCA	Principal Component Analysis
PRISMA	Preferred Reporting Items for Systematic reviews and Meta-Analyses
PV	Photovoltaic
RA	Relative Agreement (algorithm)
RE	Renewable Energy
SD	Standard Deviation
SE	Standard Error
SH	Sustainable Heating
SLR	Systematic Literature Review
SSW	Sum of Squared Weights
TEC	Therman Energy Community
TPB	Theory of Planned Behaviour
VAT	Value Added Tax
VvE	Vereniging van Eigenaren (Owners' Association)
WoON	WoonOnderzoek Nederland (Dutch Housing Survey)

1. Introduction

1.1. Motivation

Improving energy efficiency in residential buildings is vital for mitigating climate change and energy crises. In Europe, nearly 75% of existing buildings are inefficient, and 85-95% will still be in use by 2050 (European Commission, 2024). In many countries across Europe, such as the Netherlands, the space heating and hot water infrastructure relies heavily on natural gas, leading to significant dependence on cheap natural gas imports. With 63.5% of building energy used for space heating, there's a pressing need to reduce this through energy-efficient retrofitting (EER) of buildings.

Despite the benefits of retrofitting, such as reduced energy consumption and lower greenhouse gas emissions, adoption rates remain low (Publications Office of the European Union, 2019). For instance, the European Commission's Renovation Wave initiative highlights that only 1% of buildings undergo energy-efficient renovation each year, far below the rate needed to meet climate targets (European Commission, 2020). This indicates that existing policy instruments have failed to sufficiently motivate or incentivise homeowners to enhance their homes' energy efficiency.

In light of this, there is a significant gap in understanding the decision-making processes of homeowners regarding building retrofits. Homeowners, who make up 70% of the EU population (Eurostat, 2023b), are traditionally viewed as rational economic decisions (i.e. a homeowner retrofits to save money and chooses the most cost-optimal renovation measure), studies show that psychological and social factors also play a significant role (Kastner and Stern, 2015; Fowlie et al., 2015; Ebrahimigharehbaghi et al., 2020; Lang et al., 2021). Homeowners often renovate if they perceive it as necessary or improving their quality of life (Ebrahimigharehbaghi et al., 2022; Wilson et al., 2015; Organ et al., 2013; Abreu et al., 2020; Azizi et al., 2019). Major barriers for renovation are the complexity of applying for grants and lack of awareness and uncertainty about the cost of renovation (Ebrahimigharehbaghi et al., 2019; Wilson et al., 2018). Factors like energy independence, thermal comfort, and environmental impact strongly influence retrofit decisions, while demographic variables have ambiguous effects (Kastner and Stern, 2015). Hence, understanding their decision-making processes is crucial for increasing retrofitting rates and achieving sustainability goals.

Policymakers require robust, evidence-based advice to formulate and implement strategies that can effectively encourage retrofitting. Initially, energy system models focused on techno-economic aspects of building decarbonisation (Senkpiel et al., 2020; Huckebrink and Bertsch, 2021), providing detailed technological representations for policy support. These models, often using bottom-up approaches, study policy scenarios (McKenna et al., 2013; Heeren et al., 2013; Sandberg et al., 2017), support energy planning (Reinhart and Cerezo Davila, 2016; Torabi Moghadam et al., 2017) or evaluate retrofit strategies (Fonseca et al., 2016). However, they lack interaction with homeowners' decision-making processes (Nägeli et al., 2020). Although these models have been the cornerstone of policy advisement, they often fall short by focusing primarily on financial and technical aspects while neglecting crucial socio-psychological factors that significantly influence decision-making processes (Michelsen and Madlener, 2013; Wilson et al., 2015).

With the pressing need for energy transition, integrating social aspects of retrofit adoption has become essential. Agent-based models (ABMs) now simulate homeowners' decision-making, incorporating psychological and social factors. While most ABMs focus on single technologies (Du et al., 2022), predominantly on solar panels (PV) (Zhang et al., 2022; Moncada et al., 2021; Nuñez-Jimenez et al., 2020; Mittal et al., 2019a; Pearce and Slade, 2018; Palmer et al., 2015; Rai and Robinson, 2015; Zhao et al., 2011)[1]. Few

[1] For comprehensive reviews of agent-based models of energy technology adoption, see Du et al. (2022), Akhatova et al. (2022), Hesselink and Chappin (2019), Zhang and Vorobeychik (2019), Moglia et al. (2017), and Kiesling et al. (2012)

study retrofit adoption as a combination (or packages) of several retrofit measures, such as insulation and heating system replacement (Derkenbaeva et al., 2023; Nava-Guerrero et al., 2021; Nägeli et al., 2020; Moglia et al., 2018). Many ABM studies consider either heating systems (Du et al., 2024; Meles and Ryan, 2022; Sopha et al., 2013) or insulation (Friege et al., 2016; Chersoni et al., 2022) adoptions independently. Studying these together is crucial as they influence each other, like heat pumps performing better in well-insulated houses. Our research contributes to this integrated approach.

1.2. Research questions

The aim of this thesis is to explore and enhance our understanding of energy-efficient retrofitting adoption among homeowners through a multi-dimensional approach. This involves two key goals: first, to understand what drives or hinders homeowners' decisions to retrofit, and second, to model these decision-making processes to simulate the impact of policy interventions. By combining empirical analysis with agent-based modeling (ABM), this thesis not only explores the socio-economic factors influencing retrofit decisions but also evaluates the effectiveness of different policy strategies for increasing adoption.

To address this aim, three contributions are made, each associated with a specific research question (RQ). These contributions build on one another, starting with understanding homeowner behavior, followed by modeling the decision-making process, and finally, evaluating the effectiveness of these models in influencing energy-efficient retrofitting. They are based on three first-author publications[2] in scientific journals respectively: *Who invests in energy retrofits? Mining Dutch homeowners' data* (Akhatova et al., 2024), *Agent-Based Modelling of Urban District Energy System Decarbonisation—A Systematic Literature* Review (Akhatova et al., 2022), and *Agent-based modelling of building retrofit adoption in neighborhood* (Akhatova and Kranzl, 2024).

[2]Akhatova and Kranzl, 2024 is at the point of the submission of this thesis – October 16, 2024 – under review (major revision)

The first contribution of this thesis is an empirical analysis of the factors associated with decisions to adopt energy-efficient retrofits, such as window double-glazing, insulation, solar panel adoption, and heat pump installation. Using data from a Dutch household survey, the analysis identifies which homeowners are more likely to implement these measures. The findings provide insights into homeowner demographics, socio-economic status, and attitudes, and offer policy recommendations to improve energy efficient retrofit adoption.

Research question 1: *What kind of homeowners adopt building retrofitting (in the Netherlands)?* (Akhatova et al., 2024)

This research question focuses on identifying the key factors that influence homeowners' decisions to retrofit their homes with energy-efficient measures such as insulation, solar panels, and heat pumps. The goal is to provide a detailed understanding of the drivers and barriers that guide homeowners in making these decisions.

From a modeling perspective, it is crucial that the insights derived from empirical data analysis are effectively integrated into energy economic models that inform policy-making. Agent-based modeling (ABM) is gaining recognition among modellers due to its capacity to simulate each agent individually, offering a detailed view of agent behaviors, decision-making processes, and interactions (Gilbert and Troitzsch, 2005; Bonabeau, 2002; Epstein and Axtell, 1996). ABM was selected as it allows for a detailed representation of individual behaviors and their interactions within a system, making it suitable for modeling complex decision-making processes. This literature review analyses how ABM has been applied in the field and highlights the factors that need to be considered during ABM, including model purpose and outputs, agent types and attributes, decision rules, interactions, the technologies and policies modeled, the representation of spatial and temporal aspects, and the empirical grounding of the models.

Research question 2: *How has ABM been used to model policy interventions that facilitate the decarbonisation (i.e., energy transition) of building-related urban district energy systems?* (Akhatova et al., 2022)

By reviewing existing ABM applications, this research question explores the potential of ABM to simulate energy-efficient retrofit adoption. It highlights how ABM can model the interactions between agents and considers which factors (e.g., socio-economic, psychological) need to be included to improve the accuracy and applicability of these models.

The third contribution of this thesis is a comparative analysis of techno-economic and socio-psychological decision-making models and their impacts on energy demand within a small neighborhood. Techno-economic models typically focus on financial and technical factors, such as cost savings, payback periods, and technological feasibility, to predict retrofit adoption. In contrast, socio-psychological models consider social factors, such as attitudes and social norms, which influence homeowner decisions. This research compares two decision-making models—techno-economic and socio-psychological—within the ABM framework to assess which factors (financial vs. behavioral) have the greatest influence on retrofit adoption.

Research question 3: *How do techno-economic and socio-psychological decision-making rationales impact energy-efficient retrofitting adoption?* (Akhatova and Kranzl, 2024)

This research question uses ABM to evaluate how different decision-making frameworks affect retrofit adoption rates and energy demand outcomes. By modeling both economic incentives and psychological factors, this analysis highlights the importance of addressing not only financial barriers but also behavioral and social influences in policy design.

The relationship between the research questions, objectives, and the overall aim of this thesis is illustrated in Figure 1.1.

1.3. Overview of methods

To address Research Question 1, this thesis employs a combination of statistical and econometric approaches, with a focus on Principal Component

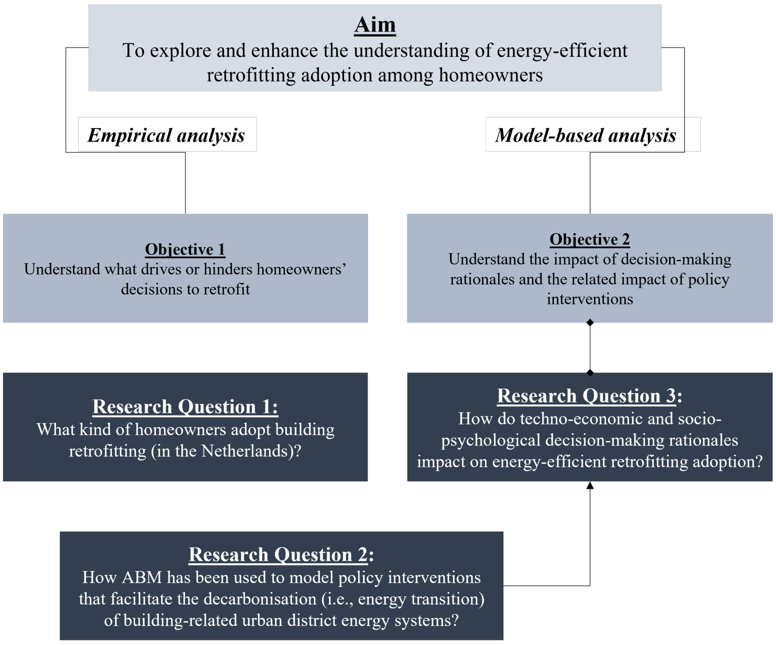

Figure 1.1.: The relationship between aim, objectives, and research questions

Analysis (PCA). PCA is utilised to reduce the dimensionality of the data from a Dutch household survey by identifying key components that represent underlying patterns in retrofit decision-making. These components are then incorporated into logistic regression models to predict the likelihood of different types of retrofit adoption, such as window double-glazing, insulation, solar panels, and heat pumps. This methodological approach provides a detailed and robust framework for understanding the factors driving retrofit decisions, thereby informing policy recommendations.

To address Research Question 2, a systematic literature review was conducted following PRISMA guidelines. This method involved a rigorous process of identifying, selecting, and synthesising relevant literature on energy-efficient retrofit adoption and ABM in energy research. The review focused on various criteria, including the purpose and outputs of models, agent types and attributes, decision rules, interactions, the technologies and policies modeled, and the representation of spatial and temporal aspects. By systematically analysing existing studies, this review highlighted gaps in the literature, provided context for the empirical and modeling work, and established a foundation for developing more integrated and holistic models of homeowner decision-making in retrofit adoption.

To address Research Question 3, Agent-Based Modeling (ABM) was utilised to simulate the decision-making processes of homeowners regarding energy-efficient retrofitting. ABM allows for the detailed representation of individual agents (homeowners) and their interactions, capturing the heterogeneity in behavior and decision-making processes. In this thesis, ABM was used to model two different decision-making strategies—techno-economic and socio-psychological—and their impact on retrofit uptake. The models incorporated various attributes, such as agent preferences, financial considerations, and social influences. By comparing the outcomes of these strategies, the ABM provided valuable insights into the effectiveness of different policy interventions and highlighted the importance of incorporating socio-psychological factors into energy-economic models.

1.4. Structure of the thesis

Based on the research questions outlined above, the remainder of this thesis is structured as follows.

Chapter 2 reviews the most relevant literature on all the topics addressed in this thesis. It begins by 55 defining key building retrofit measures and discussing European and Dutch policies aimed at promoting energy-efficient retrofitting among homeowners. The chapter then examines how literature has explored homeowner decision-making regarding retrofits, identifying factors associated with retrofit adoption and how these decisions have been modeled in energy economic studies.

Chapter 3 addresses the first research question, aiming to enhance understanding of the key drivers behind energy-efficient retrofit (EER) decisions. This is accomplished through a systematic literature review (SLR), principal component analysis (PCA), and binary logistic regression. The chapter provides a robust approach to synthesising evidence-based recommendations, which can be used to refine policies that encourage EER adoption.

Chapter 4 addresses the second research question by exploring the use of agent-based modeling (ABM) in energy research. Through a systematic literature review (SLR) following PRISMA guidelines, the chapter qualitatively analyses selected papers based on various criteria, including model purpose and outputs, agent types and attributes, decision rules, interactions, technologies and policies modelled, and the representation of spatial and temporal aspects, as well as empirical grounding of models.

Chapter 5 addresses the third research question by employing the ABM approach to model two homeowner decision-making strategies regarding retrofit adoption in a typical Dutch neighborhood. This chapter presents the methodology, results, interpretations, and overall conclusions of the modeling exercise, highlighting the differences between the two decision-making logics in terms of retrofit uptake.

Chapter 6 synthesises the key findings of this thesis, critically discussing the results in relation to the three research questions. It discusses the key results in the context of existing literature, outlines the limitations of the study, and suggests specific directions for future research, suggesting ways to build on the insights gained from this work to further enhance our understanding of energy-efficient retrofitting and urban energy transitions.

Chapter 7 concludes the thesis by summarising the main contributions, offering a broader outlook on the implications of the findings for the field of energy-efficient retrofitting, and providing general recommendations for future work and policy development.

2. State of the art and progress beyond

2.1. Building retrofit measures and policies

2.1.1. Building retrofit

Retrofit actions enhance the building or its components to exceed the initial standards set for the building. For instance, replacing single-glazed windows with sealed double-glazed units is a retrofitting action that enhances energy conservation by reducing heat loss (Jaggs and Palmer, 2000). Additionally, these new windows improve indoor environmental quality by reducing drafts, enhancing noise insulation, and boosting the building's aesthetics, thereby benefiting the occupants (Jaggs and Palmer, 2000).

According to the goal, building retrofit strategies can be categorised in four main groups (Felius et al., 2020; Rabani et al., 2017):

1. *Measures for reduction of energy demand*: actions concerning modifications to building envelope and design aspects, such as improving thermal properties, reducing infiltration and minimise thermal bridges.
2. *Measures for lowering energy consumption*: actions regarding enhancement of building systems and installations, such as installing efficient Heating, Ventilation, and Air Conditioning (HVAC) systems, improvement of domestic appliances and of electrical lighting systems.
3. *Measures for improving monitoring and controlling the energy use*: actions associating with building services and management tools, such as

monitor and control of building during operation, utilisation of metering services, clock controls, sensors, etc.

4. *reducing consumed fossil fuel*: comprised of replacing fossil by renewable energy carriers (e.g heat pump, solar panels, biomass boilers) and storing excess energy.

These retrofit measures can be implemented either as single measures or as packages (Chidiac et al., 2011). The choice depends on various factors, including the specific goals of the retrofit, the building's current condition, available budget, and the potential for energy savings. Single measures are often easier to implement, less expensive upfront, and can provide quick energy savings. Packages of measures involve a combination of multiple retrofit actions implemented together. When multiple measures are implemented together, they often complement each other, resulting in greater energy savings. For instance, combining insulation upgrades with window replacements and HVAC system enhancements can lead to better overall efficiency than implementing these measures individually.

The European Commission (EC) advocates for the development of standardised deep energy retrofit packages that ensure reliable performance and quality while appealing to homeowners and investors (International Energy Agency, 2016; European Commission, 2012). The main idea is that having pre-defined packages simplifies the process for both potential investors and the architects or construction companies involved (Shaikh et al., 2017). Analytically, these pre-defined packages make it easier to assess the cost-effectiveness of energy-saving strategies through scenario analyses (Streicher et al., 2020). Pre-defined retrofit packages simplify the decision-making process for homeowners and investors by providing a clear, comprehensive solution rather than requiring them to choose and coordinate multiple single measures. The combined implementation often reduces labor and material costs compared to conducting multiple individual projects.

Retrofit packages often align well with regulatory requirements and energy performance standards, ensuring buildings meet or exceed these standards. Besides the packages developed by European member states, various public and private energy labels offer deep-energy retrofit packages, such as the

EnerPHit label by the Passive House Institute (Passivhaus Institut, n.d.; Bastian et al., 2022) and the KfW "Effizienzhaus" in Germany (EnBW, 2024), as well as the MINERGIE system solutions in Switzerland (Minergie, 2024). Importantly, bundling measures into packages does not necessitate implementing all measures simultaneously; buildings can be retrofitted in stages over several years due to budget constraints or tax considerations (Streicher et al., 2020; Maia et al., 2021). This step-by-step retrofit approach is further supported by the concept of Renovation Passports, which provide a tailored, long-term renovation roadmap for buildings. These passports ensure that each step contributes to an overall strategy for achieving deep renovations and facilitate the gradual implementation of energy-saving measures, offering flexibility while maintaining a clear path toward significant energy reductions (Maia et al., 2021). Conversely, Energiesprong promotes a single-stage implementation using pre-fabricated modules for a complete home retrofit (Energiesprong, 2024). After an Energiesprong retrofit, a home is net-zero energy, generating the total amount of energy required for heating, hot water, and electrical appliances.

Renovations are often combined with planned maintenance of buildings, as materials degrade over time, requiring systematic upkeep and improvements. This approach ensures the longevity and efficiency of the building while optimising costs. Nägeli et al. (2019) emphasise the integration of maintenance schedules with energy renovation strategies, highlighting cost savings and enhanced building performance. Hummel et al. (2021) discuss the synergistic benefits of combining maintenance with retrofits, improving overall sustainability. Additionally, the Invert/EE-Lab model by Kranzl et al. (2013) and Müller (2015) provides a framework for simulating the impacts of combined maintenance and retrofit measures on building energy performance. This holistic approach not only extends the life of building materials but also maximises energy efficiency and economic benefits. Farahani et al. (2019) presents methods for synchronising maintenance schedules with energy renovation plans, highlighting significant cost savings and enhanced building performance.

Space heating is the largest energy-consuming activity in buildings, with many households relying on natural gas not only for heating but also for hot water and cooking needs (International Energy Agency, 2023). However, at least half of the existing residential and commercial buildings are in urgent need of deep, comprehensive renovations to lower their energy demand (Femenías et al., 2018; Jensen et al., 2018). Retrofit measures can be categorised into two main groups: those aimed at reducing energy demand and those focused on reducing energy consumption[1]. For example, heat pumps, which consume three to five times less energy than typical gas boilers, present a significant opportunity for reducing energy consumption. According to the European Heat Pump Association (EHPA), heat pump sales have been growing for the last ten years, before falling in 2023 (compared to 2022) (European Heat Pump Association, 2024b). One of the main reasons for the slowdown is the shift in policies and support mechanisms. This can be clearly observed in contrasting cases such as the Netherlands, where consistent policy support has fueled growth, and Italy, where a significant change in the support structure has undermined consumer confidence (European Heat Pump Association, 2024b). Despite this slowdown heat pumps are gaining market share on fossil fuel boilers, as seen in Figure 2.1.

Improved building insulation enhances the overall energy efficiency of heat pump systems. Insulation reduces the heat loss in a building, leading to a lower heating demand, allowing the heat pump to operate more efficiently at lower temperatures (Carroll et al., 2020; ENERGY STAR, 2024). According to International Energy Agency (2022a), implementing passive measures such as improving the building envelope is a critical first step in enhancing thermal performance, which directly supports the efficiency of high-efficiency HVAC systems like heat pumps. This approach is also emphasised in the Energy

[1]In the context of EN ISO 52000-1, the terms "energy demand" and "energy consumption" are defined as part of the framework for assessing the energy performance of buildings. Energy Demand refers to the total amount of energy required by a building to fulfill its intended use. This encompasses the energy needed for heating, cooling, ventilation, hot water, and lighting, among other uses. The demand is calculated based on the conditions and activities within the building, assuming standard operating conditions and indoor climate settings. Energy Consumption refers to the actual amount of energy consumed by the building during operation. This includes the energy delivered to the building from external sources (like electricity or gas) as well as any energy generated on-site (such as from solar panels) and used directly within the building. The consumption figure accounts for all energy flows necessary to meet the building's energy demand but may differ from the demand due to factors like system inefficiencies or behavioral variations in usage (CivilNode, 2018; REHVA Journal, 2019).

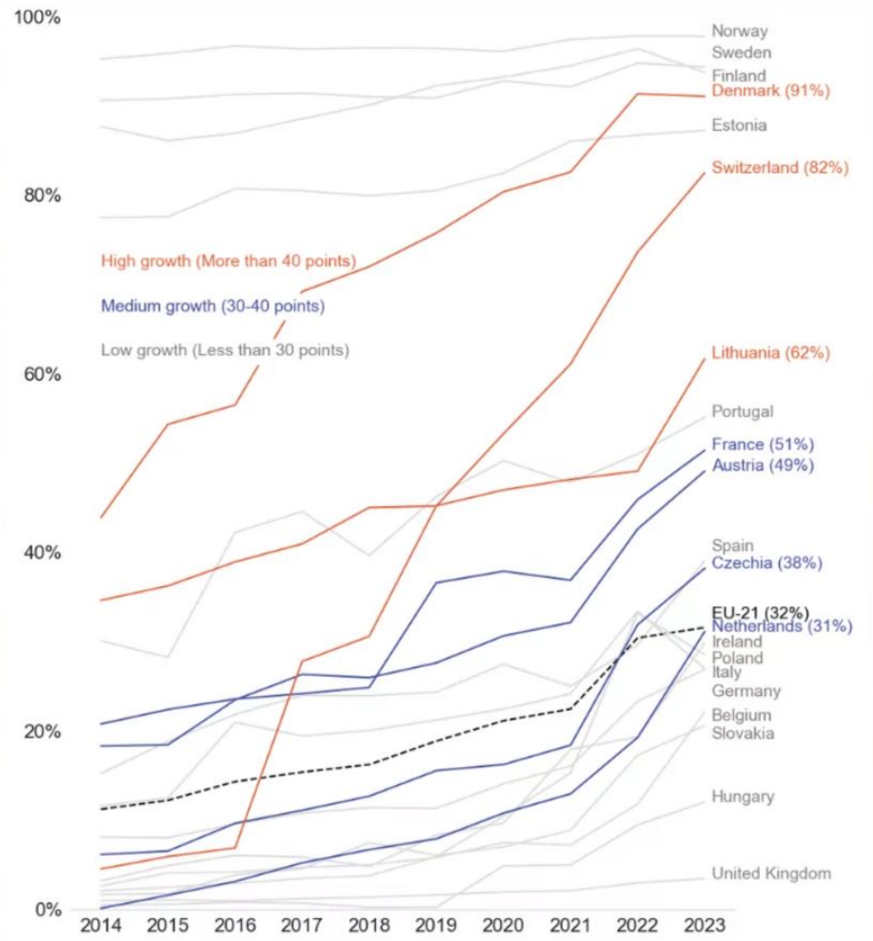

Figure 2.1.: Heat pumps' market share of the space heating market over time (European Heat Pump Association, 2024b)

Performance of Buildings Directive (EPBD, 2024/1275), which advocates for enhancing building insulation to reduce energy consumption and improve overall performance during renovations (European Commission, 2024). Enhanced insulation not only helps in reducing the heating load but also ensures that the heat generated by the pumps is retained within the building, leading to lower operational costs and improved indoor comfort. The IEA's special report on the future of heat pumps highlights the importance of integrating energy efficiency measures, such as insulation, with the deployment of heat pumps to achieve significant energy savings and reduce greenhouse gas emissions (International Energy Agency, 2022b).

By focusing on combined retrofit packages that include both insulation and the installation of heat pumps, buildings can achieve better energy performance, lower utility bills, and contribute to broader climate objectives. This holistic approach ensures that the benefits of high-efficiency technologies like heat pumps are fully realised, making it a strategic priority for building renovations in the coming years.

2.1.2. Policies to promote energy-efficient retrofit adoption

EU regulations play a crucial role in shaping the policies and initiatives in the residential and service sectors. The key legislative frameworks guiding energy efficiency in buildings are the 2024 Energy Performance of Buildings Directive (EPBD, EU/2024/1275) and the 2023 Energy Efficiency Directive (EED, EU/2023/1791). The EED has a broader scope that covers overall energy efficiency across all sectors of the economy, including industry, transportation, and buildings. It aims to improve overall energy efficiency across the EU, contributing to the EU's climate goals by reducing energy consumption, enhancing energy security, and supporting the transition to a sustainable energy system. The EPBD specifically targets the energy performance of buildings. It sets requirements for the construction of new buildings and the renovation of existing buildings to improve energy efficiency, with a strong focus on reducing energy consumption and promoting the use of renewable energy sources within the building sector.

The 2024 revision of the Energy Performance of Buildings Directive (EPBD), codified as Directive (EU) 2024/1275, introduced several significant changes from its previous version, Directive (EU) 2018/844. These changes reflect the European Union's heightened ambition to achieve climate neutrality by 2050 and to accelerate the decarbonisation of the building sector. Especially, in relation to the existing building stock, it introduces Minimum Energy Performance Standards (MEPS) for the worst-performing non-residential buildings and establishes renovation passports, which provide a detailed plan for building upgrades, and establishes one-stop shops to offer technical assistance and guidance, making it easier for building owners to undertake energy efficiency renovations.

As for the new EED (EU/2023/1791), it places greater emphasis on the public sector, mandating a 3% annual renovation rate for public buildings to improve energy performance, a target that was less stringent in earlier legislation. Furthermore, the 2023 directive introduces enhanced measures to support vulnerable populations and addresses energy poverty, ensuring that the transition to greater energy efficiency is socially equitable.

There is considerable variation in how policy packages are implemented across different Member States though, both in terms of the total number of policies enacted and the types of policies used. Laes et al. (2018) conducted a review of various panel data studies at the national level, which sought to evaluate the ex-post effects of different policies or policy packages on energy consumption within the residential sector. Germany focuses on regulatory and financial measures, setting strict energy standards for buildings and offering subsidies and loans for compliance and renovations. Finland emphasises informational and motivational strategies, running campaigns and providing resources to encourage energy-saving behaviors. Romania prioritises regulatory measures, enforcing laws that mandate specific energy-saving technologies. The Netherlands primarily relies on financial incentives, such as grants and tax breaks, to promote energy efficiency in homes.

Recently, several European countries have begun phasing out gas boilers, reflecting their commitment to reducing greenhouse gas emissions and transitioning to more sustainable energy sources. For example, France, Austria and Ireland has banned the installation of gas boilers in new buildings starting from 2023 (European Heat Pump Association, 2023c). Some countries have extended the ban on new installations of gas boilers to include existing homes. Ireland plans to extend the ban to existing homes by 2025 (European Heat Pump Association, 2023c). Germany is planning to phase out new installations of gas boilers in existing buildings by 2026, with the aim that any new heating systems installed after 2024 must use at least 65% renewable energy (European Heat Pump Association, 2023c). Denmark is planning to phase out all gas boilers by 2029, replacing them with district heating or heat pumps (European Heat Pump Association, 2023c).

The Netherlands, a country where gas boilers have traditionally dominated residential heating, has taken a strong stance by banning gas boiler connections in new buildings since 2018. In 2022 the Dutch government introduced a standard that requires the installation of hybrid heat pumps when replacing existing gas boilers, starting from 2026. Most ground-level homes will need to switch to hybrid heat pumps, which typically pay for themselves within seven years (Rijksoverheid, 2023). Exceptions include situations where the standard cannot be properly applied due to noise requirements, necessary home adjustments, or disproportionately high costs, such as when a district heating solution is expected within ten years (Rijksoverheid, 2024). Monuments and apartments are also excluded due to complex permit procedures and noise concerns (Rijksoverheid, 2024).

The energy crisis, which started in 2021, has led to higher residential gas heating prices, accelerating heat pump adoption in 2022, supported by government policies, such as decreasing electricity prices and subsidising heat pumps (European Heat Pump Association, 2024b). However, complete gas boiler bans face resistance due to high upfront costs, existing gas infrastructure, and cost-of-living pressures (Müller et al., 2024). Even with subsidies, the initial investment required for heat pumps and the need to replace existing gas infrastructure pose significant challenges for many households (European Heat Pump Association, 2023c). In response to these challenges, several countries have delayed the implementation of gas boiler bans. For example, the Netherlands, which has been at the forefront of the transition to renewable heating, has recently postponed its plans for a complete phase-out of gas boilers (Kabinetsformatie, 2024; European Heat Pump Association, 2024a). This delay highlights the complexity of the transition, especially in areas where existing gas infrastructure is still deeply embedded and where the costs of switching to alternative heating systems are high. Nevertheless, despite these delays, the overall trend indicates a steady acceleration towards reducing reliance on natural gas in residential heating, driven by both economic pressures and environmental policies (European Heat Pump Association, 2023c).

According to a review of policies modelled using ABM (Hesselink and Chappin, 2019), subsidies appear to be most effective for technologies where high initial costs and limited access to capital are the primary barriers to adoption, such as electric vehicles (EV) and heat pumps. However, in the case of technologies like solar PV, lighting, and Micro-CHP (Combined Heat and Power) plants, subsidies are less effective. This indicates that for these technologies, other obstacles, such as user inertia and the influence of social comparisons, are more significant than the financial barriers related to upfront costs (Hesselink and Chappin, 2019). Additionally, a study by Claudy et al. (2011) supports the idea that non-financial barriers, such as the perceived complexity of installation or maintenance, and the lack of information, often outweigh the financial considerations in the adoption of certain technologies. This further underscores the need for a multifaceted approach to policy design that addresses both financial and non-financial barriers. In conclusion, while subsidies are crucial for lowering the barriers to adoption for high-cost technologies like EVs and heat pumps, they must be part of a broader strategy that also addresses behavioral and informational barriers to effectively promote the uptake of other energy-efficient technologies such as solar PV, lighting, and Micro-CHP systems.

2.2. Homeowner decision-making regarding retrofit

2.2.1. Overview

Understanding the decision-making processes of homeowners is crucial for designing effective policies and programs that encourage retrofitting. This knowledge enables businesses and service providers to tailor their marketing strategies, products, and services to meet homeowners' specific needs and preferences, thus contributing to broader climate and sustainability goals (International Energy Agency, 2023). Additionally, well-designed programs can ensure equitable access to retrofitting opportunities, addressing energy poverty and promoting social equity (Ürge-Vorsatz and Tirado Herrero, 2012). Governments are increasingly using behavioural insights to improve the effectiveness of policy. For instance, a better understanding of behaviour can help encourage insulation uptake, increase policy compliance and convince citizens to act on implementing energy efficiency measures. The 2022 energy crisis sparked a rapid roll out of energy saving campaigns aimed at shielding consumers from skyrocketing prices and energy supply risks.

A group of literature supports the idea that homeowners' decision-making regarding EER is a multi-stage process. The decision-making processes described in studies by Broers et al. (2019), Pettifor et al. (2015), and Wilson et al. (2018) are grounded in Rogers's five-stage innovation decision-making process. Similar models are discussed in Ebrahimigharehbaghi et al. (2019) and further developed in Ebrahimigharehbaghi et al. (2020). An adapted decision-making model from Du et al. (2022) is illustrated in Figure 2.2. This model begins with a preliminary "not considering" stage, where households are either unaware of EER or lack adoption intentions. The "getting interested" stage follows, indicating households' awareness and consideration of EER as an option. In the 'gaining knowledge' stage, households acquire information about EER, which can be hindered by inadequate knowledge but facilitated by personalised audits. The planning stage involves gathering detailed information and seeking professional advice, with financial constraints posing potential barriers. In the decision stage, households decide whether to adopt EER, with information acquisition and professional consultation being

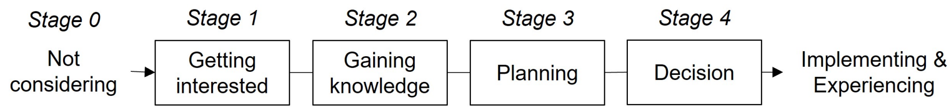

Figure 2.2.: A decision-making model (Du et al., 2022)

significant transaction costs. Following the decision, households implement and experience EER, where difficulties faced by architects and contractors can lead to negative perceptions and hinder EER diffusion.

The next section elaborates on the factors that are commonly associated with retrofit adoption. Section 2.2.2 is the outcome of a systematic literature review conducted within the author's research (Akhatova et al., 2024).

2.2.2. Factors associated with retrofit adoption decisions

2.2.2.1. Socio-demographic variables

Homeowners' age is one of the often studied variables in examining decisions about EER (Kastner and Stern, 2015; Schulte et al., 2022), with contradictory conclusions. Most of the reviewed articles report a negative relationship; that is, the older the homeowners are, the less likely they are to adopt EER (Michelsen and Madlener, 2012; Achtnicht and Madlener, 2014; Ameli and Brandt, 2015; Mortensen et al., 2016; Hecher et al., 2017; Engelken et al., 2018; Räihä and Ruokamo, 2021). Most of these studies deals with heating system preferences, e.g., heat pumps, and wood pellets heating. On the contrary, several articles suggest a positive correlation between age and the likelihood of energy retrofitting, i.e., older homeowners are more likely to insulate (Ameli and Brandt, 2015), install energy-efficient windows (EEW) (Ameli and Brandt, 2015; Ebrahimigharehbaghi et al., 2021), and invest in sustainable heating (pellet, heat pump, etc.) (Mahapatra and Gustavsson, 2010). On the other hand, other studies identify that some age groups are more likely to renovate than others. For example, in Spain, retired people and people close to retirement show a higher propensity for insulation than the middle-aged and young groups (Fernandez-Luzuriaga et al., 2022), whereas in Sweden and the Netherlands, middle-aged groups are more likely to insulate (Nair et al., 2010a; Halleck Vega et al., 2022) or install PV (De Groote et al., 2016; Halleck Vega et al., 2022).

Similarly, homeowner's *income* demonstrates mixed outcomes. In all observed studies, income shows a positive correlation with decisions to insulate (Ameli and Brandt, 2015; Schleich, 2019; Fernandez-Luzuriaga et al., 2022), install EEW (Ameli and Brandt, 2015; Schleich, 2019), adopt a more sustainable heating system (e.g., ground heating (Ruokamo, 2016), or install a heat pump (Mahapatra and Gustavsson, 2010; Michelsen and Madlener, 2012; Ruokamo, 2016). However, this correlation differs across income categories that are important for adoption. As such, while lower-income households are more likely to invest in EEW in the Netherlands (Ebrahimigharehbaghi et al., 2021) and thermal insulation in rural Poland (Kaya et al., 2021), Azizi et al. (2019) and Mortensen et al. (2016) highlight that medium- and medium-high-income homeowners are more likely to undertake energy efficiency improvements.

The *education* level is also among the often-studied predictors of EER adoption. Homeowners with higher education levels are more likely to insulate (Nair et al., 2010a; Achtnicht and Madlener, 2014; Kaya et al., 2021; Halleck Vega et al., 2022), to install heat pumps (Michelsen and Madlener, 2012) or solar panels (Ebrahimigharehbaghi et al., 2021; Halleck Vega et al., 2022) or EEW (Halleck Vega et al., 2022). Education level of a homeowner is negatively correlated only with adopting wood pellet heating (Michelsen and Madlener, 2012; Michelsen and Madlener, 2013; Ruokamo, 2016; Räihä and Ruokamo, 2021). Ruokamo (2016) suggests it could be due to the high maintenance needed for this type of heating.

Regarding *family composition*, couples with children are most likely to invest in EER (Trotta, 2018b; Ebrahimigharehbaghi et al., 2021). This may be correlated with household size (i.e., the number of people in a household), as De Groote et al. (2016) demonstrate that homes with 3 or 4 inhabitants adopt PV the most. Furthermore, Ameli and Brandt (2015) identify that household size positively correlates with the probability of investing in PV. However, results from Poland indicate that the likelihood to insulate decreases as a number of people in the household increases (Kaya et al., 2021).

Length of residence, the time a homeowner has been living in a corresponding dwelling, is a more consistent predictor of renovating. Many studies conclude that the shorter the residence time, the more likely the homeowners are to retrofit (Mortensen et al., 2016; Azizi et al., 2019). It holds in the case of EEW installation (Nair et al., 2012; Ameli and Brandt, 2015), insulation (Ameli and Brandt, 2015), and solar panel purchase (Halleck Vega et al., 2022). This might be related to the tendency to improve a new dwelling after moving in, which could be part of adapting a new dwelling for own needs (Wilson et al., 2015; Friege et al., 2016).

2.2.2.2. Dwelling characteristics

Building age positively correlates with renovating decisions (Mortensen et al., 2016; Azizi et al., 2019). It is especially evident for insulation and replacing windows with more energy-efficient ones (Nair et al., 2010b; Achtnicht and Madlener, 2014; Schleich, 2019). Heat pumps are installed in newer houses (Michelsen and Madlener, 2012). For solar panels, the adoption rate decreased with the house age; most adoptions occurred in homes built after 2000 (De Groote et al., 2016). Several works find no linear relationship between construction year and the probabilities to invest in retrofitting and that houses of some construction year categories are more likely to invest (Trotta, 2018b; Ebrahimigharehbaghi et al., 2021; Halleck Vega et al., 2022).

Building type is a significant predictor of the probability of investing in EER, with single-family houses having a higher probability. Several studies show that detached and semi-detached homes are more likely to invest in different types of renovation (Ameli and Brandt, 2015; De Groote et al., 2016; Curtis et al., 2018; Trotta, 2018b; Schleich, 2019; Ebrahimigharehbaghi et al., 2021; Halleck Vega et al., 2022).

Home size, or surface *area*, also shows mostly a positive relationship, as larger houses are more likely to install heat pumps (Michelsen and Madlener, 2012) and other sustainable heating systems (Räihä and Ruokamo, 2021), insulation (Kaya et al., 2021) and PV (De Groote et al., 2016). Only Halleck Vega et al. (2022) find that surface area is not significant and that bigger houses lag in EER uptake.

Homeowners who have undertaken *previous renovations* (not only energy-efficient ones) are more likely to invest in EER (Nair et al., 2010b; Kaya et al., 2021; Räihä and Ruokamo, 2021; Ebrahimigharehbaghi et al., 2021). However, if the heating system is relatively new (i.e., after 2000), homeowners are not considering installing a different heating system (Achtnicht and Madlener, 2014). In addition, (Ameli and Brandt, 2015) find that homeowners who perform low-cost conservation measures are more likely to invest in renewables or EER.

Some studies find that the *location of residence* can indicate the likelihood of renovating. Within specific countries, there are different levels of EER uptake. For example, in Sweden, Småland and the islands were more likely to insulate due to energy efficiency being promoted since the 1990s (Nair et al., 2010a). Stockholm county and North-Central Sweden were less likely to insulate compared to other parts of the country (Nair et al., 2010a). In Germany, east Germans are more likely to insulate (Achtnicht and Madlener, 2014) and install heat pumps (Michelsen and Madlener, 2012), while the south of Germany has a low probability of choosing heat pump but a high probability to choose pellet heating (Michelsen and Madlener, 2012).

Several articles relate this difference in adoptions to the *level of urbanisation*. For example, Halleck Vega et al. (2022) suggest that, in comparison to highly dense city centers, more rural owners are likely to adopt PV but renew their heating systems less. Michelsen and Madlener (2012) also found that rural areas have a lower likelihood of adopting heat pumps. Trotta (2018b) suggests that households living in London are 3% less likely to invest in insulation, sustainable heating, or EEW than households living in the North East region. The author assumes that low uptake in London could be due to more favorable weather conditions (less heating demand) and a busy lifestyle, i.e., “hassle factor” (Trotta, 2018b).

2.2.2.3. Motivational and other social factors

Ebrahimigharehbaghi et al. (2021) suggest that nothing motivates homeowners more than the *necessity to renovate*, e.g., when a heating system is broken. However, this might be because most renovations were related to replacing the gas heating system in the Dutch household survey 2018 that the authors used in their study. Similarly, Nair et al. (2012) observed that homeowners replaced the windows with EEW because they were too old. On the contrary, if homeowners do not see the need to renovate, for example, if they think that their dwellings are already energy-efficient, they are less likely to invest in EER (Achtnicht and Madlener, 2014; Halleck Vega et al., 2022).

Improved comfort is one of the essential motivations for renovation (Ebrahimigharehbaghi et al., 2021), as well as a value of homeowner, such that when comfort is considered necessary to homeowners or they experience discomfort, both the probability of and interest in renovating increases (Nair et al., 2010a; Klöckner and Nayum, 2017; Baumhof et al., 2018). Moreover, the belief that measures improved comfort is an essential predictor of undertaking those EER measures (Middelkoop et al., 2017). In the reviewed works, it is found to be relevant for heat pumps (Michelsen and Madlener, 2012; Decker and Menrad, 2015).

Often economic motives are correlated with decisions to renovate. For example, homeowners tend to renovate when they desire to *save costs on energy bills* (Nair et al., 2012; Engelken et al., 2018; Ebrahimigharehbaghi et al., 2021). This usually happens when households perceive their current energy bills as too high (Nair et al., 2010a; Hecher et al., 2017) or expect the prices to rise in the future (Achtnicht and Madlener, 2014). Homeowners who have plans to move and sell their dwellings in the next few years are significantly less likely to implement renovations (Azizi et al., 2019; Halleck Vega et al., 2022), as they are not planning to enjoy the benefits of renovation (such as comfort or saved energy costs).

There are other external factors that may facilitate the EER uptake, such as *subsidies* and *grants*. Subsidising PV is effective, as it increases the adoption rate (De Groote et al., 2016). The probability of choosing alternative heating systems increases significantly for subsidy recipients (Hecher et al., 2017). In addition, receiving subsidies increased the chances of performing more than one EER (Middelkoop et al., 2017). On the other hand, Michelsen and Madlener (2012) report that subsidies did not show any significance for adopting heat pumps.

Studies show that the effect of *social influence* are underestimated and that our choices are influenced by our family, friends, neighbors, or other peers (Ebrahimigharehbaghi et al., 2021). For example, Decker and Menrad (2015) show that homeowners' likelihood of choosing a heat pump over fossil-based heating was much higher if the neighbor had a heat pump. In addition, the PV adoption is associated with the positive influence of neighbors, friends, and the community (Engelken et al., 2018). However, in some cases, discussions with friends decrease the likelihood of investing in supplementary renewable heating; for example, if the majority of friends are non-adopters (Räihä and Ruokamo, 2021).

2.2.3. Energy-economic modelling of retrofit adoption decisions

According to the seminal work by Mundaca et al. (2010), bottom-up energy-economy models are critical for evaluating ex ante energy efficiency policies by simulating the impacts of different policy instruments and resulting technological changes. These models, which represent detailed characterisations of current and emerging technologies, help in designing effective policies by assessing their potential impacts. They simulate alternative technology futures and are typically driven by macroeconomic and demographic scenarios.

In the building sector, building stock models (BSM) are analytical tools used to represent and analyse the composition, characteristics, and evolution of building stocks over time. Bottom-up building stock models are utilised to estimate the energy demand of representative archetype buildings and aggregate the results to the stock level for various purposes, including studying policy scenarios (McKenna et al., 2013; Heeren et al., 2013; Sandberg et al., 2017), supporting energy planning (Reinhart and Cerezo Davila, 2016; Torabi Moghadam et al., 2017) or evaluating retrofit strategies (Fonseca et al., 2016). They are applied at a transnational and national scales (Sartori et al., 2016; McKenna et al., 2013; Mata et al., 2014) as well as at an urban (Mastrucci et al., 2014; Österbring et al., 2016) or district scale (Fonseca et al., 2016; Nägeli et al., 2015). Most BSMs either focus on the analysis of the status quo or representation of changes in the stock primarily through assumed rates of building retrofit, technology diffusion, demolition and new construction (Mastrucci et al., 2017).

Decision-making frameworks are crucial part of bottom-up energy models, as they help models realistically represent how consumers (or adopters) and firms make energy-related decisions, considering factors like market imperfections, information asymmetry, and behavioral biases. Incorporating more realistic decision-making frameworks and behavioral determinants is crucial for improving the accuracy and reliability of the models, making them more effective for evaluating and designing energy efficiency policies that can drive technological adoption and environmental benefits.

Based on Nägeli et al. (2020), conventional energy economic bottom-up building stock models assume perfect rationality with decisions based on cost-benefit analyses. For example, McKenna et al. (2013) base the decisions to renovate on a combination of economic factors and policy scenarios. Recently, more effort has been made to make the decision-makers less rational, and more "social". Discrete-choice models evaluate decisions by considering multiple attributes of technologies and policies, reflecting consumer preferences and heterogeneity. Giraudet et al. (2012) the probability of choosing a specific option is determined by sigmoid function based on the NPV difference of a retrofitting option relative to an average retrofit measure. Kranzl et al. (2013) and Müller (2015) use logit approach based on heat generation costs to calculate the share of the actual installation (market share) of available retrofitting types.

BSM traditionally focuses on technological aspects, neglecting complex interactions between technology, economics, and policy. Agent-based modeling (ABM) addresses these interactions by simulating diverse actors with distinct attributes and decision processes, making it useful for modeling energy efficiency technology adoption. Hence, researchers started employing agent-based models (ABM) they enable explicit modeling of building owners' decision-making processes based on various rules and degrees of information (Senkpiel et al., 2020; Huckebrink and Bertsch, 2021). This approach allows to integrate psychological behaviour theories (see Section 4.3.3) and social interaction (such as Relative Agreement algorithm, see Section 4.3.4) to model the decisions to adopt various technologies.

Most of the retrofit adoption ABMs focus on single technologies (Du et al., 2022), predominantly on solar panels (PV) (Zhang et al., 2022; Moncada et al., 2021; Nuñez-Jimenez et al., 2020; Mittal et al., 2019b; Pearce and Slade, 2018; Palmer et al., 2015; Rai and Robinson, 2015; Zhao et al., 2011). For comprehensive reviews of agent-based models of energy technology adoption, see Du et al. (2022), Akhatova et al. (2022), Hesselink and Chappin (2019), Zhang and Vorobeychik (2019), Moglia et al. (2017), and Kiesling et al. (2012). There are few models that study retrofit adoption as a combination (or package) of several energy-efficiency measures, such as insulation and heating system replacement (Derkenbaeva et al., 2023; Nava-Guerrero et al., 2021; Nägeli et al., 2020; Moglia et al., 2018). Many ABM studies consider either heating systems (Du et al., 2024; Meles and Ryan, 2022; Sopha et al., 2013) or insulation (Friege et al., 2016; Chersoni et al., 2022) adoptions independently. It is important to study these measures together, because they influence each other, for example, heat pumps have higher efficiencies in better insulated houses with lower useful energy demand. Hence, the current work contributes to this stream of research.

2.3. Progress beyond state of the art

The research introduces an innovative approach to understanding homeowner decision-making by integrating both technical and socio-psychological factors. Traditional models often focus on economic and technical aspects, but this work incorporates behavioral insights, recognising that homeowner decisions are influenced by a complex interplay of social norms, perceived risks, and personal values. By acknowledging these socio-psychological factors, the study provides a more comprehensive understanding of the barriers and drivers of retrofit adoption. This approach leads to more effective policy recommendations that are better aligned with the real-world behaviors and motivations of homeowners, thereby improving the uptake of energy-efficient renovations.

The dissertation makes a significant contribution by conducting a comparative analysis of techno-economic versus socio-psychological decision-making logics within the context of building energy retrofits. This dual approach highlights how different factors influence adoption rates and the effectiveness of various policy measures. While the techno-economic model primarily emphasises financial incentives and payback periods, the socio-psychological model considers behavioral aspects such as social influence and personal attitudes. This comparison reveals critical differences in how these logics affect retrofit decisions, underscoring the need for policies that address both economic and psychological barriers. Such a hybrid approach, integrating both logics, could lead to higher adoption rates and more successful policy outcomes.

This dissertation contributes to the field by focusing on combined retrofit measures in residential buildings. Instead of relying on single technologies, the research explores the combination of insulation with heating systems, such as heat pumps. This combined approach is shown to significantly enhance energy efficiency, as it addresses both heat retention through improved insulation and the efficient generation of heat. This dual strategy ensures that the energy savings are maximised, and the environmental impact is minimised, contributing to a more sustainable and resilient housing sector.

Another novel aspect of this research is the use of behaviorally-informed models to simulate the impact of various policy instruments on retrofit adoption, particularly through the inclusion of empirical data from the Netherlands on heat pump adoption. This data, used in the calibration of the models, allows for a more accurate and context-specific representation of homeowner behavior, providing insights that extend beyond theoretical constructs. The incorporation of actual adoption statistics ensures that the simulations closely reflect real-world dynamics, making the findings more applicable and reliable.

Moreover, this works improves the understanding energy-efficient retrofitting (EER) adoption among homeowners in the Netherlands by emphasising the significance of contextual factors. Unlike previous studies that often yielded contradictory results, this research focuses on the specific context within which EER decisions are made. By identifying and categorising the factors that influence homeowners' decisions to adopt measures such as insulation, photovoltaic panels (PV), and heat pumps (HP), the study provides a nuanced understanding tailored to the Dutch environment. This context-specific analysis highlights the importance of considering local conditions and homeowner characteristics when examining EER adoption.

Moreover, the empirical research pays particular attention to the characteristics of different homeowner groups, such as older, smaller households in long-owned homes. By focusing on these specific demographics, the study uncovers how these characteristics influence EER adoption and highlights the need for targeted interventions. This focus allows for the development of more precise and effective policy measures that can better address the distinct needs and challenges of these groups, ultimately contributing to a more inclusive and successful energy transition in the Netherlands.

3. Factors associated with retrofit adoption in the Netherlands

The contradictory results of previous studies on determinants of energy-efficient retrofitting (EER) adoption presented in Section 2.2.2 demonstrate that the context of each studied case is important for consideration. This chapter explores how these variables can be grouping related factors into larger components for a more comprehensive understanding the decisions to insulate, adopt photovoltaic panels (PV) or heat pump (HP). It is based on the author's article (Akhatova et al., 2024).

3.1. Overview

The urgency for energy-efficient retrofitting (EER) in buildings has intensified, driven by the need to reduce energy consumption, cut carbon emissions, and mitigate climate change, especially in light of recent gas import shortages in Europe. The residential sector, accounting for approximately 29% of final energy consumption (Enerdata, 2021), plays a crucial role in energy efficiency efforts. With owner-occupied housing making up 70.1% of the total housing stock in 2021 (eurostat, 2021), (Eurostat, 2021), the EER in this sector has become more vital than ever.

EER measures like insulation and the adoption of heat pumps or solar panels are particularly vital in colder climates, where heating accounts for a significant portion of energy demand supplied by fossil fuels. In the Netherlands, where residential buildings contribute around 14% of total greenhouse gas emissions (Ruyssenaars et al., 2021), the need for EER is pressing due to the prevalence of older, inefficient buildings and a high reliance on gas boilers. Various policies aim to encourage energy efficiency, including the Energy Performance Certificate (EPC), fiscal measures such as tax adjustments, subsidies for sustainable installations, and new initiatives like online advisory tools and district-level sustainable energy planning (European Commission, 2023; Government of the Netherlands (Rijksoverheid), 2020). Despite these efforts, many homes still have poor energy ratings, which hampers the effectiveness of heat pumps (Rijkdienst voor Ondernemend Nederland, 2021), and current policies may fall short of achieving the Green Deal's 2030 carbon reduction targets (Dijksterhuis, 2021). Therefore, understanding the factors that influence homeowners' decisions to invest in EER is crucial for aligning policies with their needs and priorities.

This study delves deeper into the factors influencing homeowners' investment decisions in EER, specifically examining four measures: window double-glazing, roof, wall and floor insulation, solar panels adoption, and heat pump installation (Akhatova et al., 2024). While existing literature in Europe underscores the complexity of these decisions, showing their association with a multitude of factors (Ameli and Brandt, 2015; Kastner and Stern, 2015; Wilson et al., 2015; Trotta, 2018a; Boomsma et al., 2019; Ebrahimigharehbaghi et al., 2021; Liu et al., 2022), there is a need to distill these into more coherent categories for better policy implications. The central contribution of this study is in clarifying the key drivers of EER-related decisions in the Netherlands, addressing the contradictory findings in existing research by consolidating correlated factors into broader components for a more insightful interpretation (Akhatova et al., 2024).

The remainder of the chapter is organised as follows. Section 3.2 presents the data and the method used for investigating the relationship between the predictors of EER adoptions. The results and discussions are addressed in Section 3.3. Finally, the chapter concludes by summarising the key insights of the study (Akhatova et al., 2024) and their policy implications in Section 3.4.

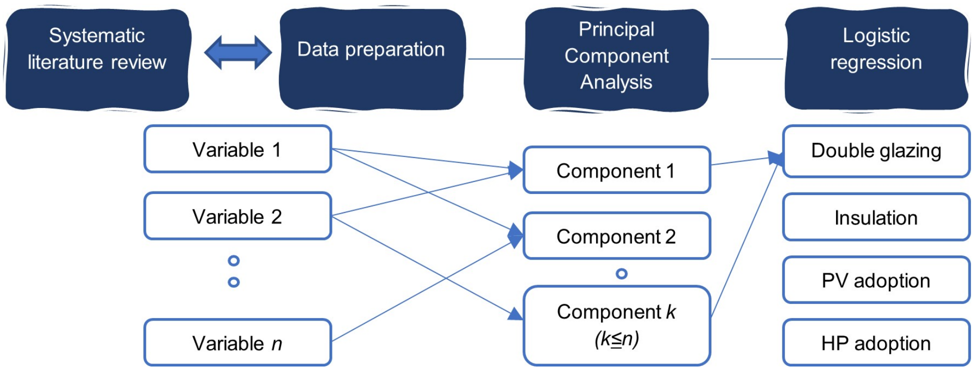

Figure 3.1.: Main steps of the empirical approach

3.2. Method

The empirical analysis relies on principal component analysis (PCA) and regression analysis. The combination of these methods is familiar as "principal component regression" and it has been known since the late 1950s (Jolliffe, 1982). The idea is to use the principal components of the original predictors in the regression instead of the original variables. As presented in Figure 3.1, first, in Section 3.2.1, actual variables from the Dutch household survey are selected based on the literature in Section 2.2.2. Second, principal components that capture the most variation in the dataset are obtained, as described in Section 3.2.2. Finally, based on the PCA scores matrix, logistic regression models for four EER decisions are performed (Section 3.2.3).

3.2.1. Data and variables

The Dutch Housing Survey WoonOnderzoek Nederland (WoON) provides information on households' characteristics, including current and desired living situation, housing costs and incomes, and energy-related information (Ministerie van Binnenlandse Zaken en Koninkrijksrelaties (Rijk), 2022). It is a nationwide survey conducted every three years and uses a stratified sample taken from all Dutch residents of 18 years old and older registered with their local municipality. Out of 46,658 total respondents, the characteristics of

25,659 homeowners are examined with a focus on their socio-demographic, dwelling, and other characteristics. Table 3.1 provides the description of the input variables for the PCA including the type (numerical, ordinal, binary), mean, standard deviation (SD), median, lowest and highest value of each variable. For categorical and binary variables frequency, histograms illustrate the proportion of relevant (category) occurrences (Figures 3.2 and 3.3). The variables used in the regression analysis as dependent variables are listed in Table 3.2.

Table 3.1.: Description of the input variables (Number of total homeowners considered N=25,659) (Ministerie van Binnenlandse Zaken en Koninkrijksrelaties (Rijk), 2022)

Variable name	Description	Variable type	Units	Mean	SD	Median	Min	Max
Length of residence	Number of years since a respondent bought a house	quantitative	Years	17.42	13.67	15	1	90
Building age	Number of years since respondent's house was constructed	quantitative	Years	51	45	44	0	1016
Income	Disposable income of household (source: CBS, 2020)	quantitative	EUR	60,471	54,750	52,896	-212,024	1,306,182
House value	Property value as evaluated periodically by municipalities, in the legal framework of the law on property values (source: WOZ, 2021)	quantitative	EUR	351,826	187,894	307,000	25,782	4,875,000
Wealth	Household's wealth defined as total assets minus liabilities (i.e., loans)	quantitative	EUR	369,426	733,446	219,226	-1,421,606	12,000,000
Usable area	Total surface area of all indoor user spaces whose highest point is at least 1.50 meters high (source: BAG, 2021)	quantitative	m^2	143	87	127	10	2,700
Electricity consumption	Annual electricity consumption (source: grid company)	quantitative	kWh/a	3,201	1,561	2,931	0	11,249
Gas consumption	Annual gas consumption (source: grid company)	quantitative	kWh/a	1,269	720	1,191	0	7,696
Age	Homeowner's age category ('17-24', '25-34', '35-44', '45-54', '55-64', '65-74', '75 and older')	ordinal (low to high)		4.54	1.54	5	1	7
Education	Homeowner's highest level of education ('low', 'medium', 'high', source: SOI 2021)	ordinal (low to high)		2.23	0.76	2	1	3

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Table 3.1.: *Continued from previous page*

Variable name	Description	Variable type	Units	Mean	SD	Median	Min	Max
Household size	Household size ('1-person' to '5 or more' people)	ordinal (low to high)		2.45	1.18	2	1	5
Urbanisation level	Urbanisation level of a neighborhood (based on the number of addresses in the surrounding, low to high)	ordinal (low to high)		3.06	1.36	3	1	5
Want to move	"Do you want to move in the next 2 years?" ('definitely not' to 'I have already found a different place')	ordinal (Likert scale)		1.44	0.85	1	1	5
Contact with neighbors	"I have a lot of contact with immediate neighbors" ('totally disagree' to 'totally agree')	ordinal (Likert scale)		3.59	1.00	4	1	5
Home satisfaction	"Satisfied with current home"	ordinal (Likert scale)		4.51	0.62	5	1	5
Environment satisfaction	"Satisfied with the living environment"	ordinal (Likert scale)		4.30	0.75	4	1	5
Neighborhood engagement	"I live in a nice neighborhood where people help each other and do things together"	ordinal (Likert scale)		3.49	0.93	4	1	5
Neighborhood insecurity	"Afraid of being harassed or robbed in this neighborhood"	ordinal (Likert scale)		1.68	0.78	2	1	5
Dwelling type	1 – apartment in a multi-family house, 0 – single-family house	dichotomous (1-yes, 0-no)		0.15	0.35	0	0	1
Past maintenance (outdoor)	Past outdoor maintenance, i.e., not necessarily energy-efficient, e.g., exterior wall work or change of window frames	dichotomous (1-yes, 0-no)		0.70	0.46	1	0	1

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Table 3.1.: *Continued from previous page*

Variable name	Description	Variable type	Units	Mean	SD	Median	Min	Max
Past maintenance (indoor)	Past indoor maintenance, e.g., kitchen or bathroom renovation or new floor	dichotomous (1-yes, 0-no)		0.49	0.50	0	0	1
Existing insulation	Existing insulation (roof, floor, walls) - beyond the past 5 years	dichotomous (1-yes, 0-no)		0.71	0.45	1	0	1
Existing double glazing	Existing double glazing (or better, e.g., triple glazing) - beyond the past 5 years	dichotomous (1-yes, 0-no)		0.71	0.45	1	0	1
Existing PV	Existing solar panels - beyond the past 5 years	dichotomous (1-yes, 0-no)		0.09	0.29	0	0	1
Existing heat pumps	Existing heat pumps - beyond the past 5 years	dichotomous (1-yes, 0-no)		0.02	0.14	0	0	1

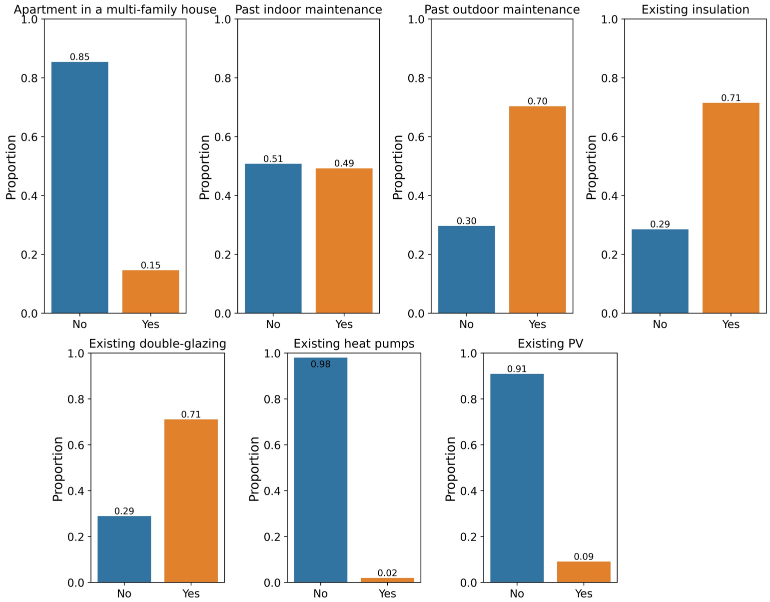

Figure 3.2.: Frequency histograms for binary variables (N=25,659)

Table 3.2.: Dependent variables

Name	Description
Adopted double glazing	A homeowner has installed double-glazed windows in the last 5 years
Adopted insulation	A homeowner has insulated a wall, roof, or floor in the last 5 years
Adopted PV	A homeowner has installed a PV panel in the last 5 years
Adopted heat pump	A homeowner has installed a heat pump in the last 5 years
	(All variables are binary/dichotomous variables with 1-Yes, 0-No)

The advantage of using the latest release is that the 2021 survey includes a new variable “heat pump adoption” that is absent in earlier releases (Ministerie van Binnenlandse Zaken en Koninkrijksrelaties (BZK); and Centraal Bureau voor de Statistiek (CBS), 2016). I argue that previously used variable “renewed boiler” (Ebrahimigharehbaghi et al., 2019; Halleck Vega et al., 2022) is not a sustainable measure, as it concerns the renewal of a gas boiler (GB).

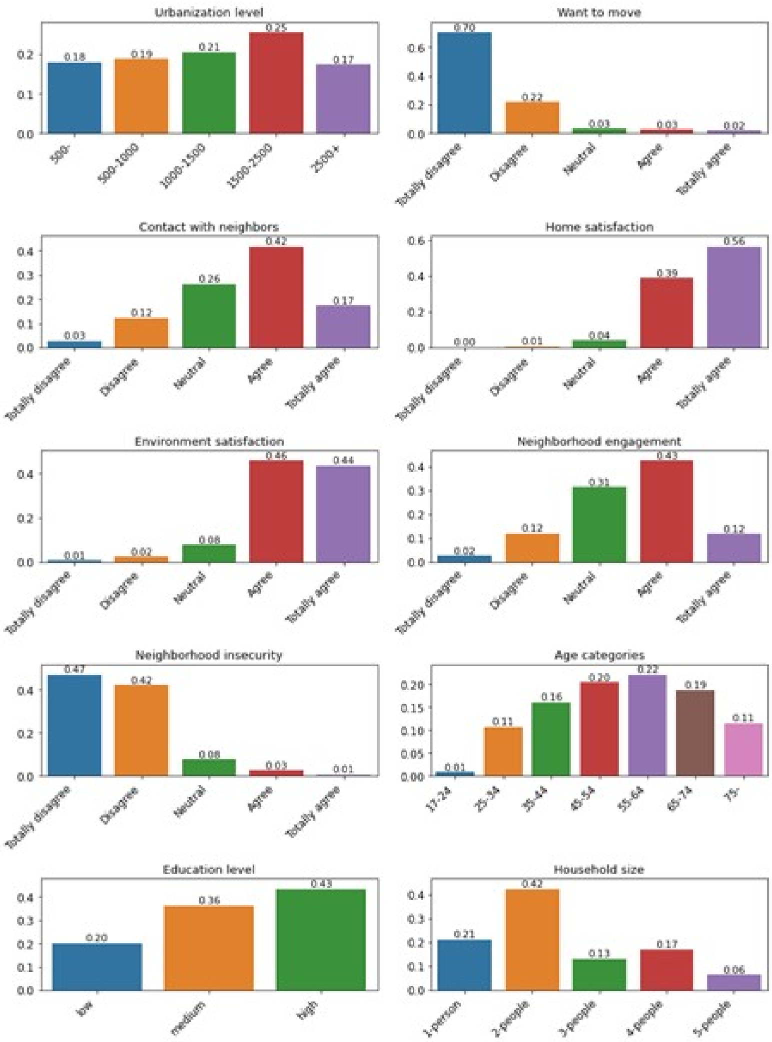

Figure 3.3.: Frequency histograms of the ordinal variables

3.2.2. Principal component analysis

PCA is a dimension reduction method which determines a few uncorrelated linear combinations of the original variables (i.e., components) that capture most of the variation in the original variables (Dunteman, 1989). Mathematically, it derives from a change of variable in linear algebra (Eq. 3.1) where original matrix of predictors X is transformed into Y, both of dimension NxK (i.e. N observations, K variables), by multiplying with an unknown matrix A (KxK):

$$Y = XA \tag{3.1}$$

The principal components (PC) are the columns of the transformation matrix A, while Y is the new matrix that represents the data in the new coordinate system defined by the PCs. The linear form of the first principal component can be described as a linear combination of K original variables $x_1, x_2, .., x_p$ (which are columns of the matrix X):

$$y_1 = a_{11}x_1 + a_{12}x_2 + \ldots + a_{1K}x_K = \sum_{i=1}^{K} a_{1i}x_i \tag{3.2}$$

Here, $a_{11}, a_{12}, .., a_{1K}$ are the loadings or weights of the first PC and they show how much each original variable x_i contributes to the first PC. The higher the loading is, the stronger the linear correlation is, while the sign indicates the direction of correlation. The first PC y_1 is derived as such that it captures the maximum variance among all linear combinations of the original variables, subject to the constraint that their squared sum (SS) is a unit vector:

$$\sum_{i=1}^{K} a_{1i}^2 = 1 \tag{3.3}$$

The columns of matrix A (or PCs), are derived via eigenvalue decomposition, sorting eigenvectors and retaining the number of PCs. Eigenvalue decomposition is a process of breaking down a matrix into its constituent parts – eigenvalues and eigenvectors. An eigenvector v of a matrix A is a vector that, when multiplied by that matrix, results in a vector that is a scaled version of the original eigenvector. This scaling is an eigenvalue (Λ) (Eq. 3.4):

$$Av = \Lambda v \tag{3.4}$$

Covariance or correlation matrix of X is used to compute them:

$$C = v\Lambda v^{-1} \tag{3.5}$$

As X contains continuous, ordinal, and dichotomous variables, the mixed correlation matrix is computed by calculating Pearson correlations for the continuous variables, polychoric correlations for ordinal (or polytomous) items, and tetrachoric correlations for the dichotomous items (see Figure 3.4) (Revelle, 2022). Then, the eigenvalues[1] and eigenvectors[2] of that mixed correlation matrix are computed and sorted in the decreasing order of the eigenvalues (i.e., by the amount of total variance explained). This ordering is crucial as it prioritises the components that explain the most variance in the data. Finally, only a subset of K variables (k, where $k < K$) are selected, such that they are sufficient to capture most of the variance in the dataset.

In practice, R package "psych" is used to calculate the PCs (Revelle, 2022). Eigenvalue decomposition and sorting are typically performed using the "principal" function of the same package, where one must specify the number of PCs and the type of rotation. The appropriate number of PCs to retain is often determined using Catell's scree plot test (Cattell, 1966), a graphical technique that plots the eigenvalues in a way that helps identify a natural cutoff point. Kaiser's criterion (Kaiser, 1974) further guides this decision, suggesting that only components with eigenvalues greater than one should be retained. This criterion is based on the logic that a principal component should explain more variance than a single standard variable (as the average eigenvalue of a standard variable is one). Therefore, by retaining components with eigenvalues above one ensures that each selected component contributes meaningfully to explaining the variance in the dataset.

[1] Represent the amount of variance that each principal component explains

[2] Define the direction of these components in the multidimensional data space

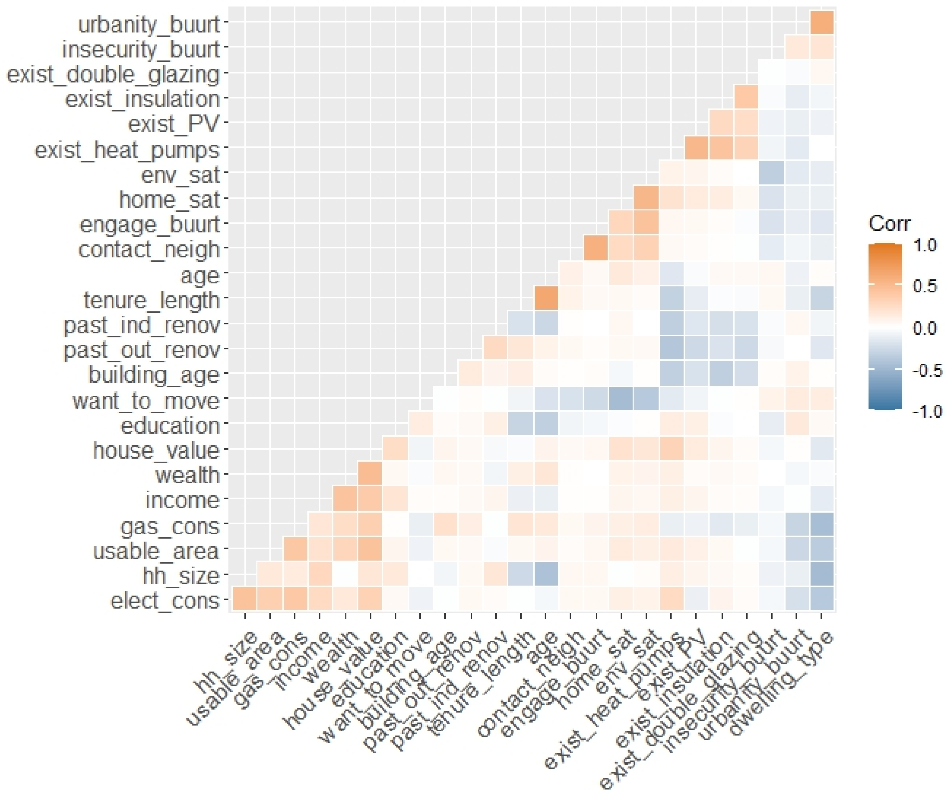

Figure 3.4.: The mixed correlation matrix

Finally, an orthogonal rotation, such as the varimax method, is applied. This step maximises the variance of each component, making the output components as distinct as possible from each other, which simplifies the interpretation. The orthogonal nature of this rotation means that the resulting components are uncorrelated with each other (Watkins, 2018).

3.2.3. Regression models

Logistic regression is used to estimate the relationship between a binary dependent variable and a number of independent variables. PCA is a viable method to address a multicollinearity problem in regression models (Dunteman, 1989; Jolliffe, 1982). This is because the components obtained by PCA are uncorrelated with each other. Principal component regression begins by using the principal component scores of the predictors as independent variables in the regression model. PCA scores represent the original data transformed into the new space defined by these components (i.e. transformed data). Mathematically, they are calculated by multiplying the zero-mean data matrix (i.e. standardised data matrix) with the matrix of the loadings or eigenvectors (Carr, 2001; Wood, 2009).

Logistic regression models are employed to ascertain the relative roles of various factors associated with the decision of homeowners to adopt each type of EER implemented in the last 5 years (2016-2021):

1. installing double-glazed windows;
2. insulation of roof, floor, and walls;
3. PV adoption, i.e., installing or replacing solar panels;
4. heat pumps adoption, i.e., installing or replacing heat pumps.

The probability of implementing a respective measure (i.e. the dependent variable Y being 1) is determined using the logistic function:

$$logit(p) = \ln \frac{p}{1-p} = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + ... + \beta_k x_k + \epsilon \tag{3.6}$$

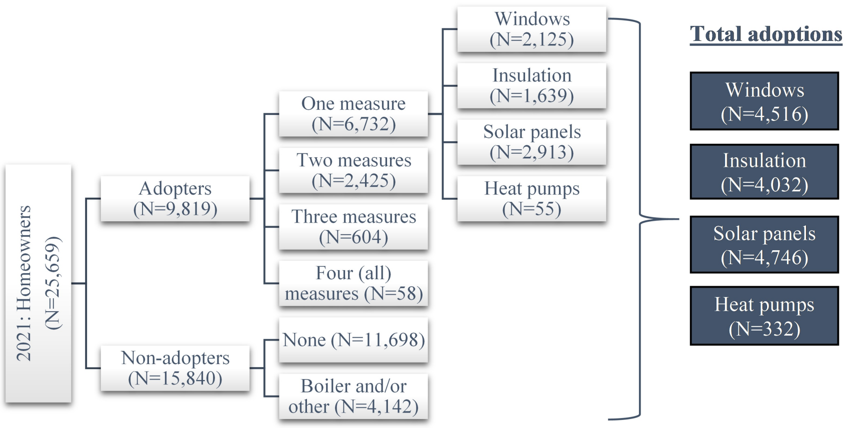

Figure 3.5.: Number of EER adopters and non-adopters; total measures adopted

where x_i denotes the scores of the principal components used as regressors. To measure the goodness of fit of the logistic regression models, McFadden pseudo R-squared is used (Domencich and McFadden, 1975). To demonstrate the model's predictive accuracy, hit rate (or correct classification rate) is calculated as the number of correct predictions divided by the total number of cases. The regression analysis was performed using the function "glm" and the package "stargazer" in R software.

3.3. Results and Discussion

3.3.1. Descriptive statistics

As summarised in Figure 3.5, out of 25,659 homeowners in the analysed sample, 38% (N=9,819) has adopted at least one EER measure. Most of these adopters implemented one (69% of adopters) or two (25% of adopters) EER types. Predominant EER types are PV or double-glazed windows, both among one-measure adopters and those who have done two or more EER measures (see "Total adoptions" in Figure 3.5).

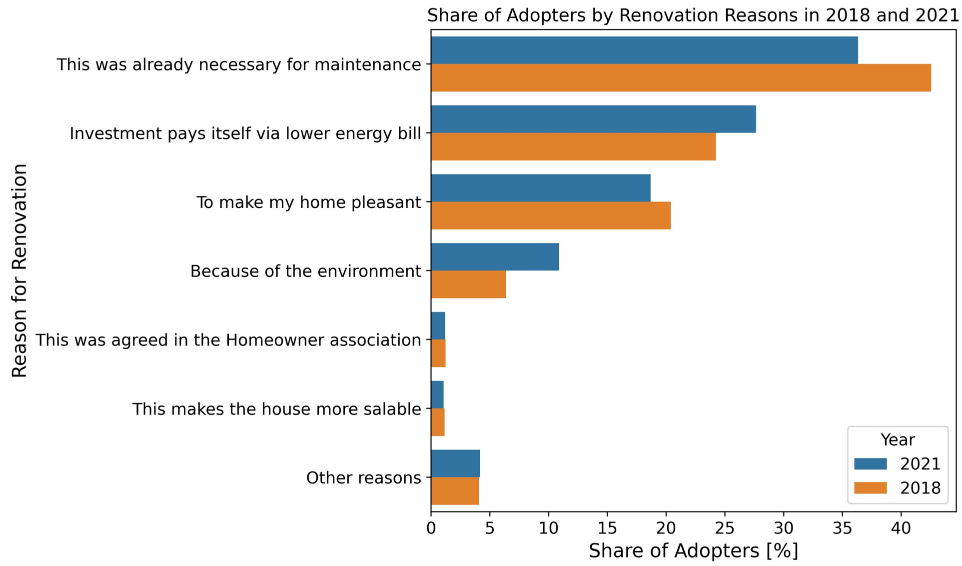

Figure 3.6.: Reasons for implementing EER among adopters. The number of total observations for this question is N=14,776 for 2021 dataset ($N_{adopters}$ = 9,819 and $N_{non-adopters}$ = 15,840) and N=23,485 for 2018 dataset ($N_{adopters}$ = 16,189 and $N_{non-adopters}$ = 21,709). The numbers show that some adopters have selected more than one reasons.

Similar to previous findings by Ebrahimigharehbaghi et al. (2019) and Ebrahimigharehbaghi et al. (2022), the majority of renovators has undertaken these EER measures because they were necessary for maintenance, to lower the energy bill and to make their home more pleasant (Figure 3.6). It is important to note that the respondents were allowed to choose several reasons for renovating (that is why the numbers do not add up to 100%). Non-adopters are hindered from renovating their dwellings mainly due to their beliefs that their homes are already energy-efficient (Figure 3.7). The share of the respondents in 2021 who have not renovated because of this is much higher than in 2018. Almost 20% of the respondents states that “they haven’t gotten around to it yet”, meaning that either they find this topic very complex or lack time and other resources to deal with this issue.

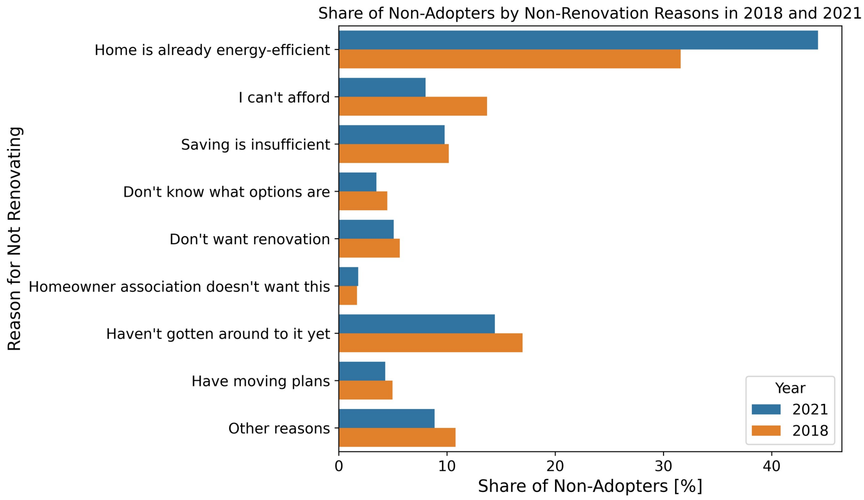

Figure 3.7.: Reasons for not implementing EER among non-adopters. The number of total observations for this question is N=13,189 for 2021 dataset ($N_{adopters}$ = 9,819 and $N_{non-adopters}$ = 15,840) and N=13,751 for 2018 dataset ($N_{adopters}$ = 16,189 and $N_{non-adopters}$ = 21,709). These numbers show that some non-adopters have not stated the reason for not renovating.

3.3.2. Characterising principal components

The PCA combines 25 variables in eight components shown in Table 3.3. The components are interpreted based on the component loading values, with higher loadings indicating a stronger (positive or negative) correlation with a corresponding component. The loadings lower than 0.35 are removed, as they are considered to be weaker determinants. The components are explained in the subsections 3.3.2.1-3.3.2.8.

3.3.2.1. Single-family houses in rural areas (PC1)

The first component refers to single-family houses in rural areas, showing that these types of homes are located in less urbanised areas and have a higher consumption of electricity and gas. These homes, which include detached, semi-detached, and terraced houses, typically have more square meters to heat and cool, and often have more appliances and electronics that consume

Table 3.3.: Component loadings

Variables	**PC1**	**PC2**	**PC3**	**PC4**	**PC5**	**PC6**	**PC7**	**PC8**
Length of residence	0.81							
Building age		-0.72						
Income	0.68							
House value	0.80							
Wealth	0.75							
Usable area	0.47	0.48						
Electricity consumption	0.54	0.39						
Gas consumption	0.58	0.37	-0.37					
Age	0.85							
Education		-0.42					0.47	
Household size	0.48		-0.60					
Contact with neighbors							0.85	
Want to move				-0.80				
Urbanisation level	-0.74							
Home satisfaction				0.80				
Environment satisfaction				0.60		0.41		
Neighborhood engagement							0.83	
Neighborhood insecurity								-0.74
Dwelling type	-0.88							
Past maintenance (outdoor)					0.74			
Past maintenance (indoor)		-0.38		0.64				
Existing insulation			0.74					
Existing double glazing			0.60					
Existing PV						-0.50		0.35
Existing heat pumps			0.45		-0.63			

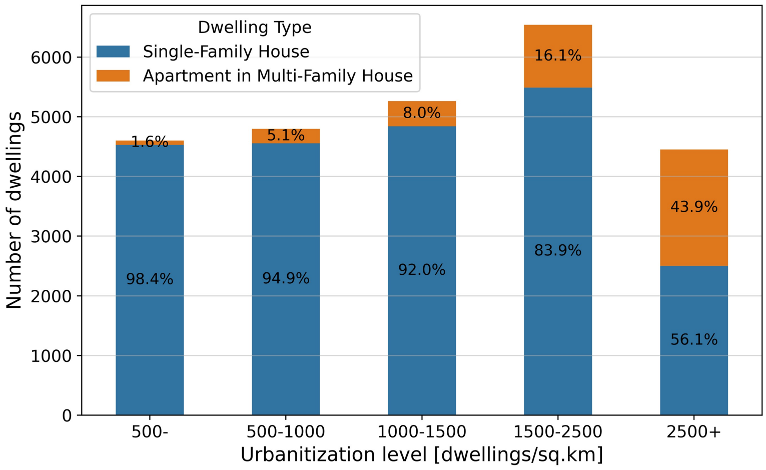

Figure 3.8.: Dwelling types by urbanisation level

energy. The location correlates with the dwelling type, as single-family houses are predominant in the suburbs and rural areas of the Netherlands (Figure 3.8). Moreover, such houses tend to be occupied by larger households with more people, e.g., families with children, which typically have higher energy consumption due to more occupants using appliances, electronics, heating, cooling, and hot water. Homes in rural areas might also engage in activities that consume more energy, such as gardening or maintaining larger outdoor spaces, which could require additional tools and equipment. Overall, this component illustrates that larger families living in larger single-family houses in rural areas have higher energy demands.

3.3.2.2. Wealthier households with larger homes (PC2)

The second component shows a positive correlation between property value, income, wealth, and home area size, indicating that financially prosperous households living in large residences. This component indicates that high income and wealthy households tend to reside in more expensive and larger homes. Despite the similar loading for 'Usable Area' as in PC1, here it is combined with indicators of financial prosperity, suggesting that wealthier households tend to occupy larger homes, which aligns with findings from

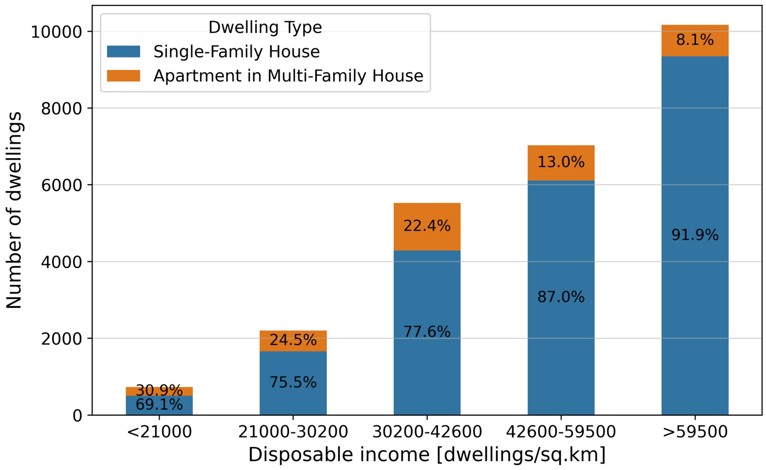

Figure 3.9.: The relationship between dwelling type and disposable income

previous studies (Büchs and Schnepf, 2013; Trotta, 2018a). Though the specific association with single-family homes may not be inferred directly from this component, Figure 3.9 demonstrates that wealthier households tend to live in single-family houses and that larger houses typically have greater needs for electricity and gas (Druckman and Jackson, 2008; Brounen et al., 2012), which justifies a weak correlation with electricity and gas consumption in this component. The similarity in the loadings for 'Usable Area' in both PC1 and PC2 (0.47 and 0.48 respectively) suggests that house size is a notable factor in both components, though leads to different interpretations.

3.3.2.3. Older, smaller households with lower education in long-owned homes (PC3)

The third component indicates positive relationship between the age of the homeowner and the length of ownership, as well as the negative relationship between these variables and the number of inhabitants and education level of homeowners. In other words, this component describes older homeowners who have owned their homes for an extended period of time. These older households tend to be smaller in size consisting of one or two inhabitants. Furthermore, this component suggests that the educational level of these homeowners is lower. The influence of education on EER decisions in this group seems to operate through mechanisms other than income, as the loading on income equals 0. One possible explanation could be related to awareness or knowledge about energy efficiency. Higher education levels often correlate with greater awareness of and access to information about energy-saving measures, which might influence the likelihood of opting for EERs (Prete et al., 2017). Another aspect could be values and attitudes that correlate with education and are not related to income. Educational experiences might shape one's environmental attitudes, which in turn influence decisions about home improvements and energy efficiency (Halleck Vega et al., 2022).

3.3.2.4. Newer houses with some EER already in place (PC4)

The fourth component depicts the relationship between building age, gas consumption, existence of insulation, energy-efficient windows, and heat pumps. This component hints that homes in more recently constructed buildings tend to already have insulation , energy-efficient windows, and heat pumps. Figure 3.10 demonstrates the proportion of households with existing insulation, which likely refers to the minimum U-value of 2.5 m2K/W set by the Building Decree (in Dutch: Bouwbesluit) in 1992 (Kieft et al., 2020). This component also shows that households living in these homes tend to have lower gas consumption, which can be attributed to the energy efficiency of the residences.

3.3.2.5. Homeowners satisfied with their homes (PC5)

The fifth component demonstrates the correlation between the owner-occupiers' satisfaction with their homes and neighborhoods and their unwillingness to move. It is clear that households who are content with their homes and surroundings have no plans for moving. When homeowners are satisfied with their homes and neighborhoods, they develop a sense of contentment and stability. The effort, cost, and emotional upheaval associated

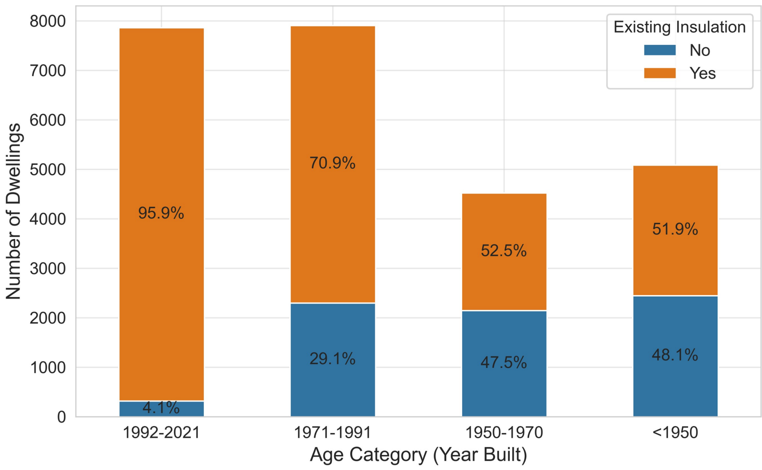

Figure 3.10.: Number of dwellings with previous insulation (adopted before 2017) vs. construction year category

with moving can be deterrents, especially when weighed against the comfort of a familiar and satisfactory living environment (Nakazato et al., 2011). Homeowners who are satisfied and not planning to move might be more inclined to invest in their properties. This includes adopting energy-efficient improvements or sustainable practices, as the benefits of such investments are realised over a longer period. In summary, the fifth component's emphasis is on the correlation between satisfaction with homes and neighborhoods and the reluctance to move highlights important aspects of residential stability and contentment.

3.3.2.6. Homes with past maintenance (PC6)

The sixth component pertains to owner-occupied residences that have undergone both past outdoor and indoor maintenance. This dimension emphasises that households that have completed outdoor maintenance and indoor maintenance are less likely to have invested in heat pumps and solar panels. Such households might have allocated their resources (budget, time, effort) primarily toward these activities. As a result, they may have limited capacity or willingness to invest further in relatively expensive energy technologies like heat pumps and solar panels in the near term. Homeowners might prioritise maintenance that addresses immediate needs or visible wear and tear, which is often more apparent in indoor and outdoor areas. In contrast, investments in HPs and PVs, while beneficial in the long run, might not be perceived as immediate or necessary improvements.

3.3.2.7. Homeowners actively engaged in their neighborhoods (PC7)

The seventh component refers to positive association between neighborhood cohesion which is characterised by contacts among neighbors, engagement in neighborhood matters and satisfaction by the living environment. It shows that homeowners actively engaged in their neighborhood by doing things together (e.g., gardening) have regular interactions with neighbors and are satisfied by the neighborhood where they live. Overall, the active engagement of homeowners in their neighborhoods is a crucial factor in building resilient, supportive, and thriving communities.

3.3.2.8. Safer neighborhoods with highly educated inhabitants (PC8)

The eighth component highlights the correlation between safer neighborhoods and highly educated inhabitants. Moreover, households in safer neighborhoods are more likely to adopt solar panels. Though higher education and higher incomes are often correlated (Psacharopoulos and Patrinos, 2018) and the sample shows more homeowners with higher education among higher income homeowners (Figure 3.11), this principal component did not capture income as a significant factor in relation to the adoption of solar panels and the perception of neighborhood safety. The adoption of solar panels and perceptions of safety might be influenced more directly by educational level and related factors, such as environmental awareness or community engagement, which can be associated with higher education but are independent of income. It is possible that in safer, more educated neighborhoods, there might be other dynamics at play, such as community initiatives, local policies, or cultural values that promote solar panel adoption, irrespective of direct

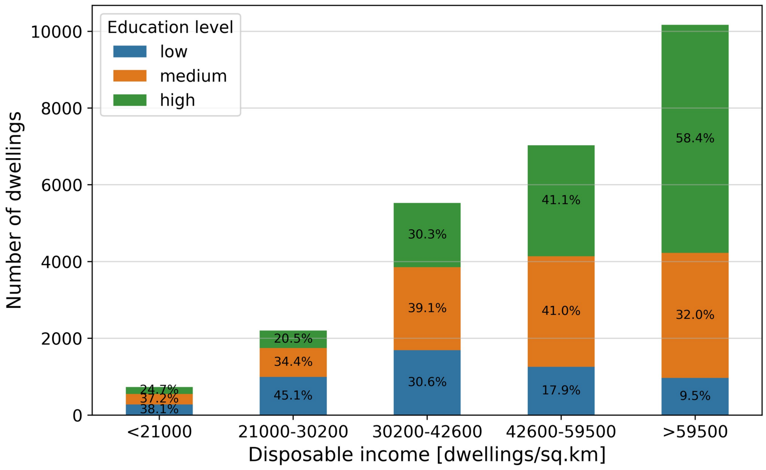

Figure 3.11.: The relationship between disposable income and education

income levels.

3.3.2.9. Summary of the PCA results

In summary, the eight extracted components[3] explain 65% of the total variance in the dataset. Variance here refers to the variability in the dataset that is captured by each principal component. Each component contributes a certain percentage to this total, with individual contribution of each component ranging from 5 to 10% (see Proportion Variance in Table 3.4). It is common practice in PCA to select the first few components that together explain a substantial portion of the total variance, often around 70%. For comparison, Michelsen and Madlener (2013) reported a cumulative variance of 61% in their study.

Table 3.4 presents the detailed breakdown of the variance explained. Let j denote the j-th principal component. The Sum of Squared Weights (SSW) for each principal component j and the proportion of variance explained by each component are as follows: for the first component (PC1), the SSW is 2.56, and

[3] The components with eigenvalues higher than one (see the scree plot in Figure 3.14) are considered.

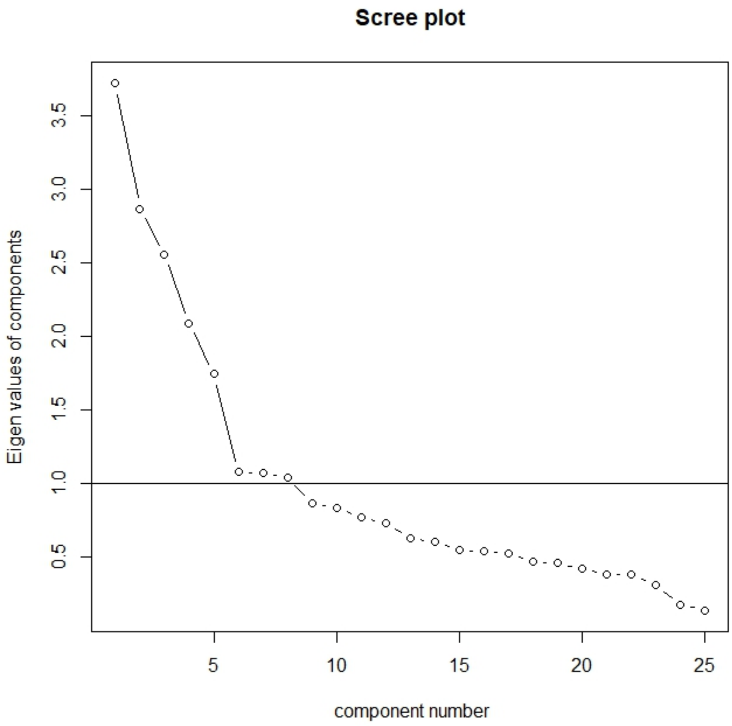

Figure 3.12.: The scree plot

it explains 10% of the total variance ($Proportion\ Variance_j = 0.10$). Similar pattern continues for the subsequent components, leading to a *Cumulative Variance*$_j$ of 0.65 by the eighth component.

3.3.3. Regression results

To uncover the factors associated with EER investment decisions, Table 3.5 presents results for double-glazing windows, roof, floor, and walls insulation, PV adoption, and HP adoption of homeowners across the Netherlands between 2016 and 2021. The results are discussed in terms of the importance of components for EER decisions (i.e., significant and high values indicate stronger likelihood).

Table 3.4.: The sum of squared weights (SSW) and variances explained by the PCA (n=8)

	PC1	PC2	PC3	PC4	PC5	PC6	PC7	PC8
SSW	2.56	2.48	2.38	2.01	1.93	1.86	1.73	1.22
Proportion Variance	0.10	0.10	0.10	0.08	0.08	0.07	0.07	0.05
Cumulative Variance	0.10	0.20	0.30	0.38	0.45	0.53	0.60	0.65

3.3.3.1. The likelihood of EER adoption by homeowners in single-family houses in rural areas

In our analysis, a strong association was observed between single-family homes in rural areas and the adoption of all EER measures, with the strongest likelihood of solar panels adoption. This finding aligns with numerous studies (Ameli and Brandt, 2015; Graziano and Gillingham, 2015; De Groote et al., 2016; Curtis et al., 2018; Trotta, 2018b; Schleich, 2019; Ebrahimigharehbaghi et al., 2022; Halleck Vega et al., 2022). One reason for this trend may be the autonomy that single-family homeowners have in making independent decisions about installing PV systems, as opposed to multi-family homes where consensus is needed due to shared infrastructure such as roofs (Milieu centraal, 2022).

Moreover, the model results indicate that these rural single-family houses are also more likely to adopt heat pumps, as well as building insulation and double-glazed windows, which further underscores the commitment of these households to energy efficiency. The preference for solar panels over heat pumps could also be attributed to the versatility and cost-effectiveness of PV systems. While the initial installation costs of PVs and HPs may be similar, PVs generate electricity, which can be used for a variety of purposes or even sold back to the grid, thereby offering potential income or cost savings.

[4] McFadden R-squared values range between 0 and 1 but are usually considerably lower than those of the R-squared. The values between 0.2-0.4 indicate excellent model fit, while values lower than 0.2 explain less variation (Domencich and McFadden, 1975).

Table 3.5.: Logistic regression results of having invested in EER over the past five years (N=25,659)

	Double-glazed windows	**Roof, floor, walls insulation**	**Solar panels**	**Heat pumps**
1. Single-family houses in rural areas	0.123*** (0.022)	0.372*** (0.027)	0.514*** (0.023)	0.439*** (0.075)
2. Wealthier households with larger homes	-0.432*** (0.023)	-0.448*** (0.026)	0.060*** (0.016)	0.313*** (0.034)
3. Older smaller households in long-owned homes	0.078*** (0.021)	0.019 (0.023)	-0.022 (0.017)	-0.317*** (0.061)
4. Newer houses with some EER already in place	-1.732*** (0.03)	-2.430*** (0.038)	0.055*** (0.02)	-0.114** (0.057)
5. Households satisfied with their homes	-0.043* (0.022)	-0.117*** (0.025)	0.271*** (0.02)	0.726*** (0.085)
6. Homes with past maintenance	1.725*** (0.04)	1.826*** (0.045)	0.428*** (0.022)	0.306*** (0.063)
7. Households actively engaged in their neighborhoods	0.003 (0.019)	0.067*** (0.022)	0.053*** (0.017)	0.06 (0.057)
8. Safer neighborhoods with highly educated inhabitants	-0.038* (0.02)	0.095*** (0.024)	0.166*** (0.018)	0.197*** (0.063)
Constant	-2.276*** (0.027)	-2.878*** (0.036)	-1.615*** (0.018)	-4.741*** (0.077)
Hit rate (Correct classification rate)	0.85	0.85	0.82	0.82
McFadden's pseudo R-squared [4]	0.242	0.366	0.053	0.072

3.3.3.2. The likelihood of EER adoption by wealthier homeowners with larger homes

The regression results suggest that wealthier households with larger homes have a lower probability of investing in double-glazed windows and insulation roof, floor, and walls, but are more likely to adopt HPs and PV systems. This could be attributed to wealthier households already living in an insulated residence with the share of existing insulation (installed prior to 2016) being higher among homeowners with higher income (Figure 3.13). Moreover, living in larger houses require higher energy demands (as seen in Section 3.3.2), where energy efficiency might be essential.

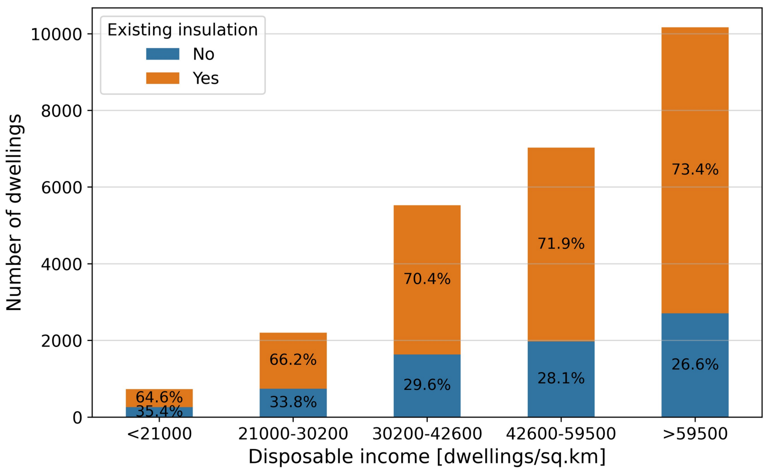

Figure 3.13.: The relationship between existing insulation and household's disposable income

3.3.3.3. The likelihood of EER adoption by older, smaller households with lower education in long-owned homes

The regression results suggest that older, smaller homeowners who have lived in their homes for a long time have a relatively high likelihood of investing in double glazing. This is in line with the findings of Nair et al. (2012) that homeowners living long in their houses with old windows are more likely to install the new ones. On the other hand, the likelihood of these households investing in HPs is negative. The negative likelihood of investing in heat pumps among this demographic group might indicate a potential income effect. HPs are often a more significant investment than window insulation and might not be deemed essential, especially if the existing heating system is adequate. Finally, the model does not indicate any correlation between these households and the adoption or non-adoption of solar panels and the insulation for roof, floor and walls.

3.3.3.4. The likelihood of EER adoption by owners of newer houses with some EER already in place

The model results indicate that there is a significant negative correlation between households living in newer houses with some EER already in place (i.e. insulation, double-glazing, and HPs) and the adoption of any type of insulation and heat pumps. This is also supported by tendency of many homeowners to consider their homes already energy-efficient (Figure 3.7). However, such houses have a slight likelihood for adopting solar panels.

3.3.3.5. The likelihood of EER adoption by homeowners satisfied with their homes

Homeowners' satisfaction with their homes is a strong predictor for investing in HPs. As they are satisfied with their homes and are not planning to move, they are more likely to invest in energy-efficiency and amelioration of their homes. The correlation between these homeowners and the adoption of PV is also significant and positive. The probability of these households adopting solar panels is high, likely for the same reasons as in the case of HPs. On the contrary, households that are satisfied with their homes are less likely to adopt the insulation of roof, floor, and walls, and to a smaller degree the window double glazing, as they have already implemented these measures in the past according to the survey responses (Figure 3.14).

3.3.3.6. The likelihood of EER adoption by owners of homes with past maintenance

The regression model shows that homeowners that have previously maintained their homes have a higher likelihood of double-glazing their windows as well as insulating their roof, floor, and walls. Since both questions were asked in retrospective manner, it is not clear whether EER and maintenance occurred in sequence or at the same time. It could be that insulation was added during maintenance projects. However, it may also be the case that

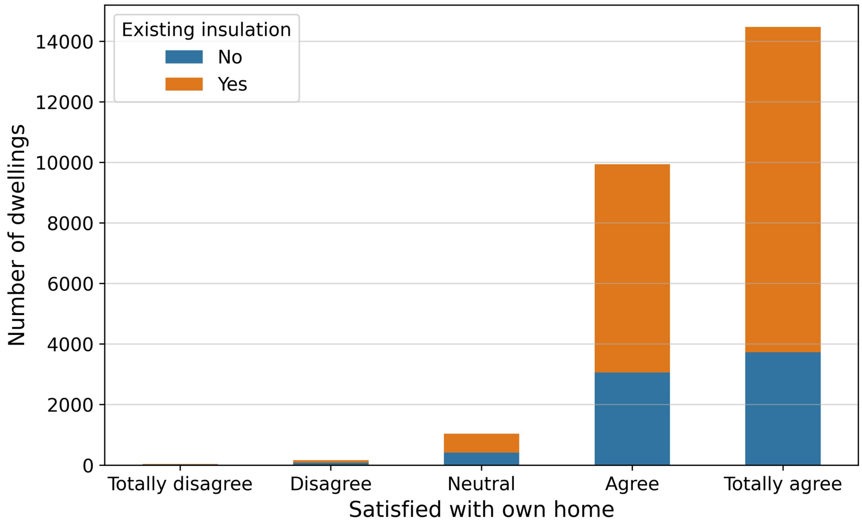

Figure 3.14.: The relationship between existing insulation and homeowner's satisfaction with home

people who put more effort maintaining their dwellings are also more aware of the energy aspects and have thus more likelihood of renovation. Homes that have undergone past maintenance also show a strong positive relationship with the adoption of HPs and solar panels, though relatively less strong than insulation and double glazing. Maintenance work and basic insulation upgrades are often seen as immediate necessities for the comfort and upkeep of a home. In contrast, the installation of solar panels and heat pumps might be viewed as optional or long-term investments.

3.3.3.7. The likelihood of EER adoption by homeowners actively engaged in their neighborhood

Interestingly, homeowners that actively participate in neighborhood cohesion show a positive correlation to the adoption of solar panels and insulation of roof, floor, and walls, although the impact size is modest compared to the other dimensions. Their active engagement with neighbors can be essential for making decisions on such investments, as they may be more likely to receive information and support for the adoption of PV systems and the extensive insulation from their community. However, the model findings indicate that households actively participating in neighborhood cohesion do not show any correlation with the adoption or non-adoption of double-glazed windows and of HPs. The contrast between the adoption of solar panels and heat pumps can be due to solar panels being often more visible and becoming symbol of environmental consciousness (Barnes et al., 2022; Bollinger et al., 2022). They can be a topic of conversation or emulation within a community, leading to a kind of “neighborhood effect”, where the adoption by one household encourages others. Conversely, the adoption of heat pumps may not have the same level of communal visibility or discussion.

3.3.3.8. The likelihood of EER adoption by homeowners in safer neighborhoods with highly educated inhabitants

The results suggest that the characteristics associated with safer neighborhoods and higher education levels, such as increased awareness of environmental issues and access to resources, might drive the adoption of solar panels, heat pumps, and insulation of roof, floor, and walls. However, in contrast to these three measures, households that are living in safer neighborhoods with highly educated residents are less likely to adopt the double-paned windows. The preference for other types of energy-efficient investments (like PV and HP) might be influenced by factors such as environmental consciousness (Halleck Vega et al., 2022), desire for modern renewable energy technologies, or visibility and status associated with these technologies (Baranzini et al., 2017).

3.3.4. Discussion, limitations and future research

This chapter offers valuable insights on factors associated with EER investment decisions among homeowners in the Netherlands. First, older, and smaller households that have lived in their homes for a long time are less likely to adopt heat pumps and show no inclination to installing solar panels or insulating their roof, floor, or walls. This trend can be partly explained by the pattern of homeowners often renovating in the early years of living in a new home as part of adapting homes to households' evolving needs (Wilson et al., 2015; Friege et al., 2016). For Dutch homeowners, necessity and the potential for energy cost savings are primary motivators for adopting EER measures. However, older homeowners in long-owned dwellings may display less propensity for such investments. This reluctance could stem from several reasons, for example, older homeowners might not anticipate significant long-term financial benefits from EER investments due to the time required to realise these returns. They may believe that the investment is not worthwhile if they do not expect to enjoy the benefits for an extended period. Moreover, there could be a reluctance to switch to new systems or technologies, especially if the existing systems are familiar and functional, even if less energy-efficient (Willis et al., 2011). It is also plausible that age-related factors, such as a desire to avoid the disruption and effort associated with significant home renovations, play a role in their decision-making process.

For older and smaller households, which often face financial constraints and may hesitate to invest in retrofitting due to concerns about upfront costs and long-term returns, a program similar to "MaPrimeRénov" in France (Agence nationale de l'habitat, 2024) would be beneficial. "MaPrimeRénov" offers substantial financial aid and comprehensive support throughout the renovation process, including initial energy audits to assess needs, assistance with applying for grants, and guidance on selecting the most effective retrofitting measures. Similarly, in the Czech Republic, the "Fix Up Grandma's House" program supports the renovation of older family homes by providing an advance subsidy and offering favorable loans to cover the remaining costs. This program aims to make renovations accessible and affordable for families, helping to modernise aging homes while also promoting energy efficiency and sustainability (IEA, 2024; Nová zelená Úsporám, 2024).

Second, households with high levels of neighborhood involvement have a positive correlation with the adoption of solar panels and insulation of roof, floor, and walls. This could be attributed to the effect of social influence on EER decisions (e.g., heat pump (Decker and Menrad, 2015) or PV (Engelken et al., 2018)) and higher trust in the community (Scheller et al., 2022). In such environments, homeowners are more likely to receive credible information and support from their neighbors, emphasising the potential for bottom-up implementation of energy transition initiatives. This observation underscores the importance of increasing awareness and making detailed information about retrofitting accessible at the community level, in addition to already existing web-tools (Milieu centraal, 2023). Furthermore, homeowners residing in safer neighborhoods with well-educated residents have a greater chance of installing solar panels and heat pumps, as well as insulating roof, floor, and walls. Satisfaction with one's home and living conditions also appears to be positively linked to the adoption of HPs and PV. Homeowners who take pride in their homes are more likely to see the value in enhancements that not only increase comfort and functionality, but also contribute to long-term energy savings and environmental sustainability. Consequently, awareness and information campaigns targeting EER should consider this aspect and communicating how EER can enhance home comfort, increase property value, and contribute to a sustainable living environment.

This suggests that policies aimed at fostering community-based retrofitting initiatives could be highly effective. For example, the Dutch government could focus on supporting and empowering a small group of individuals who can effectively lead these projects by providing centralised, organised resources and assistance (Ghorbani et al., 2020). This would help overcome leadership challenges and facilitate the successful development of Local Energy Initiatives (Ghorbani et al., 2020).

Third, single-family houses in rural areas are more likely to implement EER and especially PV adoption, which may be because they generally face fewer technical or organisational obstacles to do so. Unlike multi-family buildings, they do not share walls or roofs with neighbors, and can renovate with less hurdles (Nair et al., 2017; Palm and Reindl, 2018). In addition, it is more challenging to install PV in older city centers, due to the irregular shapes of roofs (Psacharopoulos and Patrinos, 2018). The model results also show a strong link between rural single-family homes and HPs adoption as well as building envelope insulation and windows double glazing. These homes tend to be bigger and have higher heating needs, making them more likely to adopt insulation and HPs to decrease gas usage and energy expenses. As revealed in Section 3.3.1, the majority of HP installations were done in addition to other measures. This is likely due to HPs being more effective in insulated spaces, where they don't have to work as hard to maintain a comfortable temperature (Kieft et al., 2021).

Finally, previous maintenance increases the likelihood of investing in EER. This is because homeowners who regularly maintain their homes are more likely to be informed about the potential issues and benefits of energy efficiency. However, homeowners in newer dwellings with existing insulation are less inclined to adopt insulation and HP. This suggests that these homeowners may not be receptive to those measures, possibly because they already find their homes energy-efficient and comfortable. To ensure those beliefs are objective, governments should make it compulsory to inspect the energy efficiency of each house and make this audit service available for all. On the other hand, such homeowners are more likely to adopt PV, as this can reduce the need for grid-supplied electricity, thus contributing to reduced energy bills.

There are several limitations related to this work. Not all variables identified from the literature review could be found in the studied survey. Therefore, such important predictors as awareness (e.g., about energy efficiency, available subsidies, environmental consequences) should be included in further research. Furthermore, more qualitative research unveiling the barriers of specific groups of homeowners, such as the elderly or homeowners with past maintenance, could help understand how to support or encourage these groups. In addition, conducting panel surveys instead of cross-sectional studies would be more valuable for such research, as it would allow examining the effect of new measures or a change of attitude toward EER over time. Also, energy poverty can be a significant barrier for adopting EERs and should be addressed when exploring EER-related decision-making (Mulder et al., 2023). However, as energy poverty is an important and extensive topic with no commonly agreed definition in the literature, it deserves a separate investigation that should start with defining the term, also taking into account an area context.

As the survey used in this work was conducted during the COVID-19 time, it is important to note that there are fewer observations than in previous releases. In addition, some deviations of the households' decisions are possible due to the system disruption caused by the pandemic. However, as the respondents do not specify when exactly the decisions to adopt are made, it was not possible to remove the data for these years. Therefore, it is desirable to conduct another analysis observing future changes in households' decisions caused by the energy crisis in 2022. The increasing use of EER to lower energy costs may benefit many, but unaffordability of EER may also make the situation of vulnerable populations even worse. In addition, for renewable technologies like PV there is growing issue of grid limits which hinders new connections and, thus, serve as an additional barrier for their adoptions (Brockway et al., 2021). Hence, it is imperative to study how the decisions of households changed in 2022 and what we can learn from it.

3.4. Conclusion and Policy Implications

As climate change and energy crises become more serious, the need to enhance the energy efficiency and self-sufficiency of homes becomes pressing. Our empirical analysis employing principal component analysis (PCA) and regression models not only elucidates the factors influencing homeowners' decisions on energy efficiency retrofit (EER) adoption but also provides robust data-backed insights for policymakers. Specifically, the methodological body of our work—identifying key predictors like household characteristics, neighborhood engagement, and prior maintenance activities—directly informs targeted policy interventions. To effectively catalyse EER adoption, policies that are nuanced and responsive to these predictors are recommended. For instance, the significant role of neighborhood engagement suggests that community-based information campaigns and support programs could be instrumental in enhancing EER uptake. Similarly, our findings on the influence of prior maintenance on EER decisions underscore the potential of integrating energy efficiency measures into routine maintenance frameworks. Importantly, our regression analysis highlights the nuanced dynamics among different homeowner groups, offering a data-driven basis for segment-specific policies. Therefore, I advocate for policy formulations that not only address the general barriers to EER adoption but are also customised to resonate with the unique needs and behaviors identified through our methodological analysis. By directly tying these policy implications back to our empirical findings, I aim to contribute to the development of more effective and evidence-based energy policies that can facilitate a more sustainable energy transition. A more comprehensive list of recommendations that could be of use to the Dutch government and beyond is offered below:

1. *Providing financial and technical know-how support for elderly to implement EER*

As older homeowners in long-owned homes are lagging behind in the EER adoption, government should pay more attention to these homeowners and offer them the financial and technical know-how support to implement EER in order to increase the energy efficiency in their homes. Another effective approach for local governments is to raise awareness about EER in homeowner associations and, in addition to financial aid, offer educational opportunities, free or low-cost audits, and consultations from credible experts. Online advisory tools that exist currently may not effectively reach this group of homeowners.

2. *Supporting neighborhoods with technical, financial, and regulatory assistance*

Safer and more cohesive neighborhood residents being more likely to adopt the EER indicates a promising potential for bottom-up energy transition. Therefore, the course for a neighborhood-oriented energy transition set by the Dutch government should be maintained and grassroots initiatives should be supported further not only financially, but also in terms of technical and regulatory know-how. Targeting households involved in neighborhood cohesion as early adopters can lead the way for other disadvantaged communities and enhance the government's trust with local communities. If they live in safe neighborhoods with energy-efficient and sustainable homes, people are more likely to feel secure and invest in their homes for a longer stay.

3. *Revising regulations to facilitate EER adoption in multi-family dwellings*

While single-family houses in rural areas are more likely to implement EER, the group in the opposite spectrum – apartment owners in multi-family houses in urban areas – are still hard-to-reach. Earlier studies have already shown the complexity of renovating multi-family buildings owned by several entities (i.e., condominiums). However, little has been changed or even brought to the spotlight with regards to the housing regulatory framework. It is crucial to revise housing regulations to facilitate the financing and implementation of EER measures in multi-family houses. In this regard, measures agreed in the recent EPBD recast, such as obligations to renovate the least performing buildings and providing technical and financial assistance facilities, such as one-stop-shops, would be very essential.

4. *Accessibility of targeted information in communities*

Engagement with neighbors and, subsequently community support and the exchange of information at the neighborhood level can greatly influence the adoption of EER. This understanding highlights the importance of developing localised and tailored information campaigns and engagement strategies. Such initiatives should aim to not only raise awareness, but also cater to the unique characteristics and needs of different communities, facilitating broader and more effective implementation of EER measures. These efforts are particularly relevant for homeowners contemplating renovations. Research indicates that homeowners who have previously undertaken renovations tend to be better informed about the cost-benefit aspects of retrofits, leading to a heightened motivation to improve their homes' energy efficiency, comfort, and resale value (Pardalis et al., 2021). Despite this increased interest, a significant barrier remains: many homeowners lack knowledge about reputable companies and often do not trust them to execute renovations effectively (Pardalis et al., 2021). Therefore, enhancing the accessibility of reliable information about EER measures, providing clear, trustworthy resources on EER options, reputable service providers, and tangible benefits of retrofits will significantly aid in overcoming these barriers, leading to increased energy efficiency across communities.

5. *Requiring all homeowners to obtain an energy efficiency label*

Our research confirms that homeowners living in newer houses do not tend to implement EER measures (except PV), as they believe that their homes are already energy-efficient. This is particularly representative in the Netherlands, where post-1992 construction standards have led to a baseline level of insulation and energy efficiency. However, evolving energy efficiency standards suggest a need for ongoing assessment. In this context, government interventions, such as mandatory energy efficiency surveys for all dwellings, become pertinent. These surveys, potentially subsidised by the government to ensure free access for homeowners, would assign an energy efficiency rating to each dwelling, similar to how smart meters provided by utilities help households monitor real-time energy consumption in monetary terms. Such measures could make energy costs and efficiency more tangible for homeowners. Additionally, implementing a minimum retrofitting standard, akin to those for office buildings in the Netherlands, along with punitive measures for non-compliance, could further incentivise adoption of EER measures. This comprehensive approach would ensure all homeowners, including those of older properties and inheritors of houses, are included in the energy efficiency labeling initiative, thereby addressing the gap in awareness and compliance.

In conclusion, this study identifies population groups that are still lagging behind in energy transition in the Netherlands. The policy implications derived from this research can be a valuable addition to the existing policy frameworks of the Dutch government, promoting an inclusive and equitable approach to energy transition. Moreover, the broader relevance and adaptability of these policy suggestions make them potentially applicable to other countries as well. These recommendations, emphasising the need for supporting elderly populations and local initiatives in EER implementation, revising EER regulations in multi-apartment dwellings, and enhancing awareness and requirements for energy efficiency certificates, address challenges that are common across various regions. Recognising these challenges presents a significant opportunity for policymakers worldwide to refine and adapt their strategies. By learning from the findings of this study, other areas can develop more effective and inclusive policies, thereby advancing their own energy transition goals in a way that is equitable and beneficial for all segments of their populations.

4. Review of agent-based modelling of urban district systems

This chapter aims to obtain an overview of how ABM has been used to model policy interventions that facilitate the decarbonisation (i.e., energy transition) of building-related urban district energy systems and consider stakeholders' social characteristics and interactions. It provides a comprehensive understanding of how agent-based modeling (ABM) has been applied to simulate energy transitions at the urban district level, particularly focusing on building-related energy systems. It offers a thorough exploration of how these models incorporate stakeholders and policies, delves into various modeling choices and methodologies, and identifies existing research gaps as well as potential areas for future application.

4.1. Overview

Deep decarbonisation of the building sector in the European Union (EU) is one of the key prerequisites for becoming climate neutral by 2050, as buildings account for around 40% of final energy consumption (UNEP - UN Environment Programme, 2019). In this regard, "zero energy" building concepts, which largely rely on reduced energy demand and on-site renewable generation, have recently gained considerable interest in both scientific literature (Nematchoua et al., 2021; Mittal et al., 2019a; Marique and Reiter, 2014; Marszal et al., 2011; Paiho et al., 2019; Rose et al., 2021) and in practice (Saheb et al., 2019). However, some researchers argue that dense and compact buildings on small plots have a small potential for an on-site renewable generation (Schneider et al., 2019; Nematchoua et al., 2021) and can hardly achieve zero energy balance. Thus, the expansion of building-level "zero energy" concept to the scale of neighbourhoods, districts and communities is a potential alternative solution. With this motivation, several concepts that aim to achieve zero or positive energy balance, such as Net-Zero Energy Neighbourhoods (or Districts) (Marique and Reiter, 2014; Nematchoua et al., 2021; Brozovsky et al., 2021), Plus-Energy Quarters (Schöfmann et al., 2020; Geschäftsstelle Schweiz Hauptstadtregion, 2020), and Positive Energy Districts (JPI Urban Europe, n.d.; Derkenbaeva et al., 2022; Bruck et al., 2021) are being implemented currently.

Increased interest in such neighbourhood or district-level concepts as a solution for energy and climate issues, raise a multitude of new questions, the most generic of them being: "what socio-techno-economic conditions support the transition of urban districts towards zero and positive energy districts?". More concretely, what policies, technologies and processes can foster this transition? In this context, it is becoming even more critical to understand the perspectives and roles of various stakeholders, including households, firms and public institutions, as their participation (e.g., via energy conservation, prosumption and energy trading, infrastructure development) in transitioning to a decarbonised society can be supported by well-designed and inclusive policies and programs (Klein et al., 2019; Rai and Henry, 2016).

Within a broad selection of models used in energy system analysis (Chang et al., 2021), agent-based modelling (ABM) approach is distinguished by its ability to represent individual decision-making of heterogeneous actors, as well as interactions between them (Després et al., 2015; Ringkjøb et al., 2018). Moreover, it is a simulation-type model that allows defining micro-level action and interaction rules, leading to macro-level emergent insights (Bonabeau, 2002). Hence, it is deemed suitable for exploring policy-related "what-if" questions and incorporating actors' perspectives in the energy system (Klein et al., 2019; Moglia et al., 2017; Rai and Henry, 2016).

In the following subsections, the foundations for the topic of our focus are laid down. Namely, the existing literature is studied and the urban district energy system is defined (Section 4.1.1). Secondly, the state-of-the-art of ABM's application in the energy systems research is discussed (Section 4.1.2).

4.1.1. Urban District Energy Systems and Models

The energy system is defined by the Intergovernmental Panel on Climate Change (IPCC) (Allwood et al., 2014) as: "all components related to the production, conversion, delivery, and use of energy". The energy system is also seen as a socio-technical system, comprised of more than just technical components, but also markets, institutions, consumer behaviours and other factors that affect the construction and operation of technical infrastructures (Keirstead et al., 2012).

The differentiation of energy systems into "urban" and "district" is generally about defining the system's scope. In Europe, "urban areas" refer to cities (i.e., densely populated areas), towns and suburbs (i.e., intermediate density areas), as opposed to rural (i.e., sparsely populated) areas (Eurostat, 2023a). According to the motivation and purpose of this work, the studies that address the energy system challenges of densely populated urban areas are reviewed.

Depending on various national contexts, "districts" and "neighbourhoods" can denote different administrative and non-administrative areas of cities or countries. Like Paiho et al. (2019), Rose et al. (2021), and Bottecchia et al. (2021), I do not refer to certain juridical or administrative areas, but as part of an urban area. Hence, everything from a small to a large group of buildings is considered a "district" within this work. Due to the inconsistent use of the similar terms in the literature, the synonyms of "district" such as "neighbourhood", "quarter", "block" and "community" are included in the analysis.

It is important to note though, that the search for "district energy systems" brings to district-scale energy systems, be that traditional district-level thermal and hybrid energy systems (e.g., cogeneration) (Dincer and Rosen, 2013; Dragoon, 2017; Lake et al., 2017; Nageler et al., 2019) or distributed energy systems such as PV, solar thermal, battery storage (Allegrini et al., 2015; Huang et al., 2020; Mahmoud et al., 2020; Schweiger et al., 2018). However, consistent with the above-mentioned definitions of Keirstead et al. (2012) and Allwood et al. (2014), I keep the scope of "district energy system" broader and do not limit it to the technical components only.

There are various energy system modelling approaches and tools that can be or are used at the district-scale for different purposes (Allegrini et al., 2015; Keirstead et al., 2012; Schweiger et al., 2018). As Allegrini et al. (2015) conclude about the numerous urban district-level energy models and tools: “some tools aim to provide a single simulation that addresses many issues, while others give detailed results regarding specific parts of the system”. Although the advantages of ABM in studying complex systems and enabling the analysis of policies are acknowledged (Keirstead et al., 2012; Hansen et al., 2019; Hesselink and Chappin, 2019; Rai and Henry, 2016; Castro et al., 2020), its role in studying district energy systems, to the authors’ knowledge, has not yet been explored in detail.

4.1.2. Agent-Based Modelling in Energy Systems Research

ABM is a modelling approach that can be seen as one of the applications of a software engineering paradigm named “Multi-agent systems” (MAS) (Wooldridge, 1992). (Some application fields of MAS are represented in Figure 4.1). There is an ambiguity between MAS and ABM. However, the general understanding is that MAS is an overarching architecture or paradigm, which, when applied for simulating various phenomena by abstracting real-life systems (e.g., human, animals, organisations) is usually called ABM or agent-based simulation (ABS). Whereas MAS-based engineering deals with applying the MAS architecture to create a software or control system, ABM applies MAS paradigm to draw implications about other systems (e.g., human settlements, stock markets, etc.). The common point between MAS-based engineering and ABM is in the desire to understand a complex system by assuming a distributed or autonomous behaviour instead of centralised or equation-governed behaviour of system elements (e.g., like in System Dynamics approach). Hence, the terms “multi-agent-system”, “multi-agent-based-modelling” and “agent-based modelling” are sometimes used interchangeably in the literature (Lez-Briones et al., 2018; Mahmood et al., 2017; Tomicic and Schatten, 2016; Yasir et al., 2018). However, the difference of these two approaches, namely that ABM sets up agents with characteristics of real-world

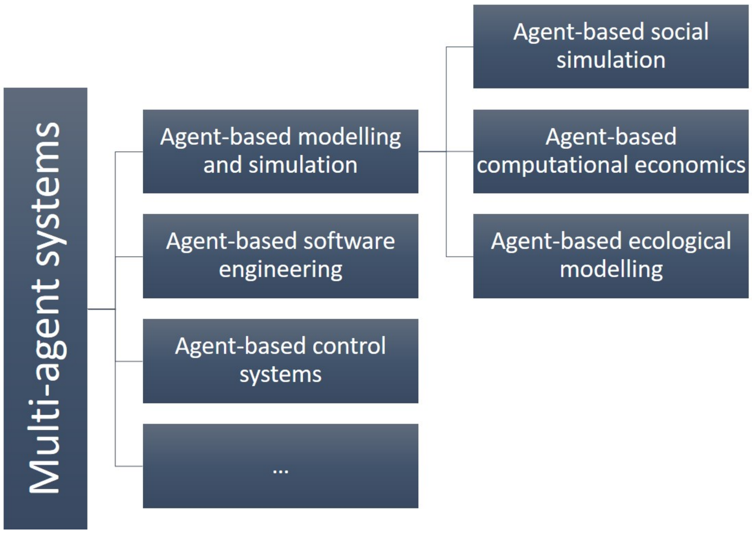

Figure 4.1.: Multi-Agent Systems

analogy to see what happens when they act, while in a multi-agent system, agents are defined with certain characteristics, connections and choices, such that they achieve specified emergent states (Dam et al., 2013).

ABM can, thus, be more specifically understood as a computer simulation of an artificial world populated by agents – discrete decision-making entities (individual, household, firm, etc.) – whose behaviours and rules of different complexity can govern interactions. One of the main reasons for choosing ABM over traditional equation-based modelling approaches in energy systems analysis (i.e., system dynamics, optimisation models, computable general equilibrium models) is its ability to incorporate heterogeneity and adaptivity of energy consumers (Weidlich and Veit, 2008). In the energy system research, this strength has been exploited for:

1. analysing the demand side of energy system (Rai and Henry, 2016), e.g., incorporating occupant behaviour in buildings (Azar et al., 2016; Azar and Al Ansari, 2017);
2. better-informing policy-making and infrastructure planning (Hesselink and Chappin, 2019; Moglia et al., 2017), e.g., determining target groups for interventions (Zarei and Maghrebi, 2020b; Zarei and Maghrebi,

2020a) or recommendations specific to the adoption of particular renewable energy or energy-efficient technologies (Mittal et al., 2019a; Boumaiza et al., 2018; Rai and Robinson, 2015).

As the number and publication date of review papers indicate (see Table 4.1, the first applications of ABM in energy research were for representing wholesale electricity markets to analyse market structures (Weidlich and Veit, 2008). The possibility of using ABM for questions related to smart electricity grids and markets, such as the integration of demand response and distributed generation in local or centralised markets, is explored by (Ringler et al., 2016). The potential of ABM to improve our understanding of consumer energy demand, by allowing to account for social, behavioural, economic, technological, and market and policy factors that influence energy demand is presented by (Rai and Henry, 2016). Questions that interest energy economists and policymakers are how consumers adopt energy-efficient technology and how to encourage them. The benefit that ABM can bring to this stream of research, as well as barriers and incentives for the adoption of energy-efficient measures in the residential sector are addressed by Hesselink and Chappin (2019) and Moglia et al. (2017). Though our review topic overlaps with theirs, I do not focus on the ABMs of "innovation diffusion" only and explore a wider range of approaches.

Table 4.1.: List of previous review articles.

Study	Focus of the Review	Type of Review	Number of Reviewed Papers	Covered Aspects	Key Conclusions
Berger and Mahdavi (2020)	Application of ABM in the built environment domain (building energy and indoor-environmental performance)	selective	23	Motivational background, approach for representation of both people (and their behaviour) and environment (e.g., case studies), implementation tools, state of ABM development and its future directions in the domain of buildings' energy and indoor-environmental performance	Motivation of the studies analyzed: to realistically capture the interactions between occupants as well as the interactions between occupants and their surrounding built environment.
Castro et al. (2020)	Application of ABM in studying climate-energy policy	selective	61	Reasons for using ABM, number and types of markets represented (e.g., transportation, electricity, financial services), empirical basis, time horizon, agent types and numbers, types of bounded rationality, social interactions and networks; link between model features and policy results	3 main themes identified: focusing on policies that (1) directly trigger emissions reduction, (2) stimulate the diffusion of low-carbon/energy products and technologies, and (3) encourage energy conservation in other ways. Research gaps are identified.

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Table 4.1.: *Continued from previous page*

Study	Focus of the Review	Type of Review	Number of Reviewed Papers	Covered Aspects	Key Conclusions
Hansen et al. (2019)	Application of ABM in the built environment domain (building energy and indoor-environmental performance)	systematic	62	Thematic analysis from a multi-level perspective of energy transitions; Modelling complexity in energy transitions (complexity categories).	6 topic areas identified: Electricity Market (25), Consumption Dynamics/ Consumer Behaviour (12), Policy and Planning (9), New Technologies/ Innovation (7), Energy System (6), Transitions (3). Application in Policy and Planning is very important (drives energy transitions).
Hesselink and Chappin (2019)	Adoption of energy efficient technologies by households	systematic	23	Technologies studied, barriers to the adoption of energy efficiency, policy measures that are explored using the ABMs, theories used to describe decision-making of households and the use of empirical data	Modelled policies: subsidies, regulation and taxation, technology ban, household adoption obligation and various information campaigns. Many of the models are rooted in the TPB, use utility functions, and/or use empirical data.

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Table 4.1.: *Continued from previous page*

Study	Focus of the Review	Type of Review	Number of Reviewed Papers	Covered Aspects	Key Conclusions
Moglia et al. (2017)	Application of ABM for understanding technology diffusion of residential energy efficient technologies and to evaluate policies' effects on adoption.	selective	-	Types of ABM approaches (both theoretical and empirical); applicability and limitations of ABM for modelling of the uptake of en-eff tech-s in energy sector	Key components of ABM for describing the adoption and key decision when intending to model the uptake of energy-efficiency technologies. ABM can model technology diffusion with at least the same accuracy as equation-based modelling when appropriately parameterised based on empirical data, calibrated based on macro-level data, and validated using sensitivity analysis.
Rai and Henry (2016)	ABM work in the area of consumer energy choices, with a focus on the demand side of energy to aid the design of better policies and programmes	selective, critical	about 60	Limitations of non-ABM approaches, framework for describing the essential features of ABM, use of ABM in practice	Two major types of energy-demand questions that ABM is well-suited to answer: those related to policy design and evaluation, and those related to system design and infrastructure planning.

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Table 4.1.: *Continued from previous page*

Study	Focus of the Review	Type of Review	Number of Reviewed Papers	Covered Aspects	Key Conclusions
Ringler et al. (2016)	Application of ABM for analysing smart grids from a systems perspective	selective	23	How ABM can be used to analyse electricity systems; typology of agent-based research of electricity systems; review of literature specifically studying smart grids using ABMS techniques is reviewed	ABM is still a limited field of research, but can deliver specific insights about how different agents in a smart grid would interact and which effects would occur on a global level. Valuable input for decision processes of stakeholders and policy making.
Weidlich and Veit (2008)	Overview of AB electricity market models and present the most relevant work in detail.	selective	31	Comparison of current AB electricity models, Methodological questions: Agent learning behavior, Market dynamics and complexity, calibration and validation, Model description and publication.	Choice of specific learning algorithms, more careful and well documented validation and verification procedures as well as the appropriate publication of details of concrete simulation models are crucial for the further development of AB electricity market modeling.

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Table 4.1.: *Continued from previous page*

Study	Focus of the Review	Type of Review	Number of Reviewed Papers	Covered Aspects	Key Conclusions
Zhou et al. (2007)	Study of the ABM simulation packages for electricity markets	selective	4	Overview of electricity markets, general-purpose ABS tools to introduce some background of ABS, detailed study of four popular ABS packages for Electricity Markets (SEPIA, EMCAS, STEMT-RT, NEMSIM).	ABS packages are divided into 2 types: toolkit (Netlogo, Repast) and software (AnyLogic, AgentSheets)

The remainder of this chapter is structured as follows. Section 4.2 provides the description of our approach for the systematic selection and review of the articles. The main results of the review are presented in Section 4.3 and organised in different thematic subsections related to essential aspects of ABMs of urban district energy systems, namely: model purpose and outputs, agents, their decision-making and interaction rules, technologies and policies covered, spatial and temporal aspects, as well as experimental setup of simulations, use of empirical data, and implementation platform used. The chapter is finalised with synthesised observations and future research suggestions in Section 4.4.

4.2. Method

This work is based on the literature review type originating in biomedical and healthcare research and becoming prominent in energy system research too (Hansen et al., 2019; Hesselink and Chappin, 2019) – systematic literature review (SLR).

The current SLR is carried out on the 13th of September, 2021 in the Scopus database only. The main research question is: "how ABM has been applied in studying the urban district (building-related) energy systems?". Accordingly, the search string provided in the PRISMA Flow diagram in Figure 4.2 reflects this question. First, the literature suggests many variations of agent-based concepts – simulations, models, approaches, as well as "multi-agent" and "multi-agent-based" simulations, models, and approaches. Although there are differences between MAS and ABM (see Section 4.1.2), they are sometimes used interchangeably in the literature. Therefore, the studies referring to "multi-agent-based" simulations were not excluded automatically but carefully checked. Second, the search term "energy OR heat*" ensures that all studies mentioning energy or heat are captured. Urban district energy systems are defined here as a group of buildings, heating and cooling infrastructure, distributed energy resources (PV, battery, solar thermal, heat pump, CHP), electricity distribution network, and energy producers, consumers, prosumers and other relevant stakeholders in a given district

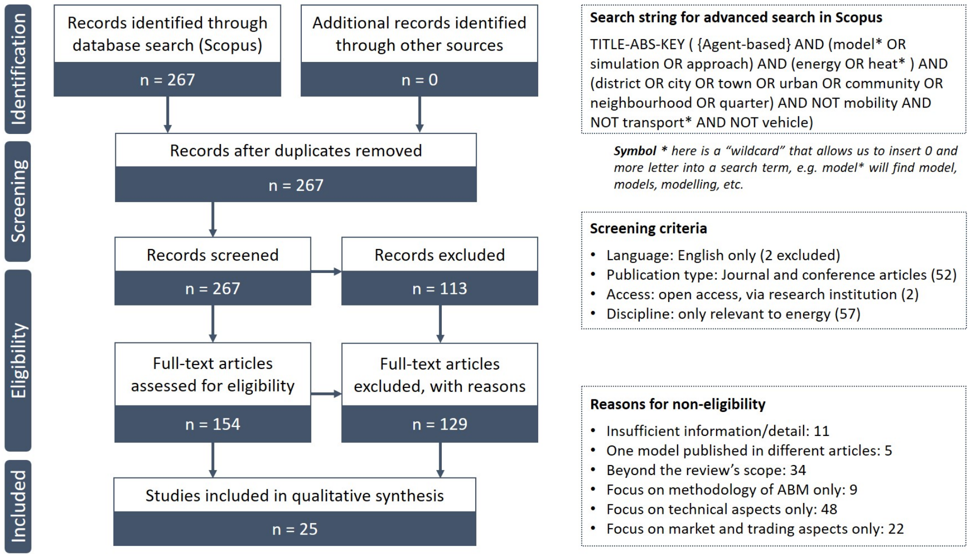

Figure 4.2.: Systematic Literature Review Process

or city. Hence, for example, transport-related studies, which returned 92 additional records in Scopus, are excluded. Third, as explained in Section 4.1.1, "district" is used interchangeably with "neighbourhood", "quarter", "block", "community". Moreover, sometimes city or town-level models are applicable to a smaller scale too. Hence, the article with at least one of the terms are considered.

After a rigorous identification in the Scopus database and removing duplicated records, further screening was performed using Scopus automatic filtering, reading titles and abstracts. Journal and conference articles, written in English, accessible either openly or the research institution's library, and relevant to the energy research were filtered out. Finally, full-text analysis has been applied to ensure the selected studies match the aim of this review (Akhatova et al., 2022). The exact reasons for exclusion together with the full SLR process are presented in Figure 4.2.

After the papers have been selected, they are qualitatively analysed based on the following key aspects of ABMs:

1. model purpose and outputs (Section 4.3.1)

2. agents (Section 4.3.2)
3. agent decision rules (Section 4.3.3)
4. agent interaction (Section 4.3.4)
5. technologies and policies modelled (Section 4.3.5)
6. spatial and temporal aspects (Section 4.3.6)
7. empirical grounding (Section 4.3.7)

As already mentioned in one of the previous review articles (Castro et al., 2020), ABMs differ strongly in how they are designed and implemented, so a quantitative comparison of models is impractical. Therefore, I focused on the qualitative description of modelling choices and methodological aspects within the selected ABMs. The defined thematic clusters of analysis were inspired by the review approaches of Ringkjøb et al. (2018) and Hesselink and Chappin (2019), as well as by the Overview, Design Concepts, and Details (ODD) protocol (Grimm et al., 2006; Grimm et al., 2010; Grimm et al., 2020) – the attempt to formalise the documentation of the ABM's modelling process and results. Whenever included or implemented, the ODD protocol improves the readability and ensures that the information needed to understand and further analyse the models is present.

Within this work, I focus on the components of the energy system related to the built environment of a district (i.e., buildings, heating, cooling, electricity supply systems) and human individuals or groups. Thus, studies focusing on other sectors (i.e., transport, industry, or agriculture and forestry) and elements (e.g., energy markets, information systems, power network) of the energy system, though recognised as part of the energy system, are outside the scope of this review (Akhatova et al., 2022).

4.3. Results

This section presents the findings from the thorough analysis of 25 studies based on model purposes and outputs, agents, their decision-making frameworks and interactions, technologies and policies covered, spatial and temporal aspects, and empirical grounding.

Diffusion ABMs

"Diffusion": dissemination of technology, practices; social learning.

Aim: to analyse adoptions of energy-efficient or renewable energy technology by households, firms and other entities, often due to certain policy interventions.

Outcomes: number of adopters or adopted units, energy or emissions saved over time.

Exploratory ABMs

Aim: to explore various novel phenomena (e.g. establishment of Thermal Energy Communities, energy-saving behaviour) and the sociotechnical conditions or policies that facilitate/hinder those.

Outcomes: specific to the purpose (e.g. number of households joining/leaving a TEC)

Figure 4.3.: Purpose of the models

4.3.1. Model Purposes and Outputs

The review by Rai and Henry (2016) highlights that ABM is well-suited to answer two kinds of energy-demand questions: those related to policy design and evaluation and those related to system design and infrastructure planning. The review process reflects the existence of these two motivations for modelling, of which I only focus on those that are relevant for policy design. These studies evaluate the agents' behavioural response to external stimuli in the form of a policy, regulation, observation or feedback, and peer influence. Rai and Robinson (2015) present a well-validated example of an ABM used to test the influence of the regulatory framework on adopting renewable technology. They examine how additional rebates (i.e., partial refund of an item's cost) for low-income households and changes in the amount of rebate, affect the adoption of rooftop PV in Austin, Texas.

A model's purpose or objective must be "clear, concise and specific" (Grimm et al., 2006), which is essential for others to understand why some aspects of reality are included in a model while others are omitted. It is because each a model should be a "purposeful" abstraction of reality (Starfield et al., 1990). The purposes of the 25 selected models are diverse. However, I identified two main thematic clusters: diffusion and exploratory ABMs (see Figure 4.3).

One large thematic cluster is the exploration of technology adoption that has its foundations in innovation diffusion theories (Kiesling et al., 2012). This type of ABM is often named "agent-based diffusion model" (Hesselink and Chappin, 2019; Moglia et al., 2017; Kiesling et al., 2012; Zhang and Vorobeychik, 2019). They aim to analyse adoptions of energy-efficient or renewable energy technology by households, firms and other entities, often due to certain policy interventions (Caprioli et al., 2020; Lee and Hong, 2019; Mehta et al., 2019; Mittal et al., 2019b; Mittal et al., 2019a; Muaafa et al., 2017; Rai and Robinson, 2015; Ramshani et al., 2020; Schiera et al., 2019). Usually, such models' outputs are the number of adopters or adopted units, energy or emissions saved over time (see Table 4.2). This approach allows us to observe what factors affect the adoptions of technologies in which ways. The term "diffusion" encompasses concepts like social learning and dissemination (Strang and Soule, 1998). Thus, this approach is also well-suited to represent the dissemination of energy-related practices and behaviours, such as energy-saving (Azar and Al Ansari, 2017; Zarei and Maghrebi, 2020a), energy-efficient ventilation behaviour (Jensen et al., 2016; Jensen and Chappin, 2017), user learning (i.e., energy saving) after authoritative smart meter adoption (Zhang et al., 2016), building renovation behaviour (Preisler et al., 2017), weatherisation (i.e., making apartments weather-proof) (Huang et al., 2019), buying energy-efficient appliances and switching an energy provider (Niamir et al., 2020). Similar to technology adoption, these studies investigate how energy-related behaviours are adopted and how much energy can be saved. Three models (Jensen et al., 2016; Jensen and Chappin, 2017; Zhang et al., 2016) focus on both technology adoption and the resulting behaviour dissemination.

Table 4.2.: Model purposes and model outputs of the selected studies – Diffusion ABMs.

Study	**Model Purpose**	**Model Output**
Azar and Al Ansari (2017)	Explore the effect of social-network characteristics on the diffusion process of energy conservation	% energy savings from different feedback methods with various social network characteristics
Boumaiza et al. (2018)	Examine the impact of information diffusion algorithm on residential PV adoption in city neighbourhoods	Number of new and total adopters over time

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Table 4.2.: *Continued from previous page*

Study	Model Purpose	Model Output
Caprioli et al. (2020)	Test alternative policy scenarios for PV adoption in a neighbourhood	Number of PV adoptions per year (simulated vs real data), spatial visualisation of total adoptions
Jensen and Chappin (2017)	Design and test marketing strategies for feedback devices (CO2-meter) to identify which would be most effective	Technology and shock ventilation behaviour adoption for different lifestyles
Jensen et al. (2016)	Identify the effect of the 'CO2 meter' (feedback device) on energy-efficient heating behaviour	Adoption numbers with various marketing strategies (awareness, give-away device, training) and their locations
Lee and Hong (2019)	Analyse diffusion patterns of rooftop PV under the influence of five factors on the adoption	Number of adopters over time; spatial representation of adoption
Mehta et al. (2019)	Explore individual and community solar PV adoption under the Energy Act in Switzerland	Installed capacity of individual and community PV systems over time
Mittal et al. (2019a)	Test consumer adoption behaviours over time in the presence of different renewable energy options	Number of adopters by renewable options, restricted households, % of neighbourhood RE
Mittal et al. (2019b)	Predict the consumer adoption of different renewable energy models and to determine the resulting impacts on energy system performance	Utility and solar installer revenues, total power added to the grid, total number of adopters, number of rooftop PV and community solar adopters over time
Muaafa et al. (2017)	Determine the effect of PV diffusion on the profitability of utilities	% of buildings with installed PV, % of new installations per year, % of demand met by PV, spatial representation of building adoption.
Niamir et al. (2020)	Observe the impact of socioeconomic heterogeneity, social dynamics, and carbon pricing on individual energy-related decisions	CO2-emissions over time; avoided CO2-emissions by each type of behaviour (investment, conservation, switching supplier)
Rai and Robinson (2015)	Test the effect of solar rebates on PV adoption	Cumulative number of PV systems over time; thematic maps with spatial distribution and density of PV systems adopted
Ramshani et al. (2020)	Determine the diffusion rate of the green technologies under uncertainties caused by climate change, characteristics of adopters, and their interactions	Number of installed technologies over time, under six different policies

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Table 4.2.: *Continued from previous page*

Study	Model Purpose	Model Output
Schiera et al. (2019)	Assess the impact of switching from the self-consumer paradigm to a jointly acting renewable community on adoption rate of rooftop PV in a city district	kW installed over time, number of new adopters per year, spatial distribution, typical daily production-consumption profile
Zhang et al. (2016)	Study user learning in authoritative technology adoption based on the case of smart meter deployment in Leeds	Average daily electricity load curve (kW), number of experienced users, agents' attitude and energy-saving awareness over time

The remaining works have more exploratory purposes and are less established than diffusion ABMs. Fouladvand et al. (2020) investigate how Thermal Energy Communities (TEC) can be formed and sustained, where agents can either join a new or existing community or decide to drop-out based on financial, technological and energy plan (e.g., self-consumption) evaluations. Busch et al. (2017) model is distinguished from other models by representing the continuous process of engagement and district-heating development instead of instantaneous decisions (e.g., to adopt, to invest). In these studies, the output metrics are very specific to the purpose and subject studies (see Table 4.3).

Table 4.3.: Model purposes and model outputs of the selected studies – Exploratory ABMs.

Study	Model Purpose	Model Output
Busch et al. (2017)	Explore the development of heat network business models by focusing on the decisions and actions of local actors in developing projects	Number of realised project by various instigators (i.e., municipal, commercial and community) over time
Fouladvand et al. (2020)	Provide insights into factors influencing the formation and continuation of TEC initiatives	% of joined households (at initiation), % of households who joined afterwards, satisfaction of the households who joined the community
Gotts and Polhill (2017)	Explore policy scenarios and campaigns aimed at reducing domestic energy demand (i.e., economic scenarios affecting energy prices and household income)	Total energy demand (in 2049), factors that affect the demand (income & fuel price growth, external influences)

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Table 4.3.: *Continued from previous page*

Study	Model Purpose	Model Output
Huang et al. (2019)	Explore the impacts of social interactions on weatherization decisions for households under pre- and post-weatherisation conditions	Number of weatherized households (with and without Assistance Program, with and without community leader, for different memory lengths of agents, and network characteristics)
Nava Guerrero et al. (2019)	Explore socioeconomic conditions that could support the neighborhoods' heat transition over time while meeting the neighbourhood's heat demand	Number of heating systems adopted at certain combination of time horizon for all, changes in natural gas price and electricity price, fraction of households that is able to compare combined investments
Nava-Guerrero et al. (2021)	Explore how group decision-making in strata buildings could affect the heat transition in the owner-occupied share of the housing sector in the Netherlands	Individual preferences for thermal systems at the beginning of the simulation, group lock out (when the Homeowner Association can't agree on the decision), cumulative heating costs over time
Preisler et al. (2017)	Explore the development of the renovation state of the building stock based on renovation behaviour of different types of homeowners	Development of overall heat demand (GWh/a) and number of buildings renovated in the city over time
Yue et al. (2020)	Analyse the effect of behavioural outcomes in different policy situation due to the influence of energy-saving behaviour and intentions	Descriptive statistical mean values of different situational factors
Zarei and Maghrebi (2020a)	Investigate participants' related factors that can affect short-term and long-term effects of these programs	Short-term (right after the eco-feedback program) and long-term (after interactions with other agents) efficiencies of the program
Zarei and Maghrebi (2020b)	Find the near-optimum targets among a social network of households in order to participate in a typical Energy Efficiency Program (EEP)	Energy Index that changes due to the EEP or the social interactions

4.3.2. Agents

Agent is a key element in this modelling approach. Many previous studies highlight that there is no common definition of an agent (MacAl and North, 2010; Ringler et al., 2016), as its properties depend on the model's purpose and application area. Nevertheless, many authors refer to the following basic definition presented by Jennings (2000): "Agent is an encapsulated computer system that is situated in some environment, and that is capable of flexible, autonomous action in that environment in order to meet its design objectives". In the ODD protocol, agents are one of the model's "entities", along with spatial units and the overall environment (Grimm et al., 2020). It is due to the parallels between the agent-based modelling approach and Object-Oriented Programming (OOP) (i.e., the "classes" or its instances in OOP could be equivalent to "entities" in ABM). It might lead to confusion among readers who are new to Agent-based modelling or use different implementation tools. In the current work, I differentiate between agents and other entities, where I refer to "agents" as autonomous entities that can make decisions (i.e., implement certain algorithms) and interact (i.e., obtain information from its environment or other agents) in order to reach its objectives.

Most of the agents in the selected studies are "households" (15 out of 25) and three studies also denote them as "energy consumers" (Mittal et al., 2019b; Niamir et al., 2020; Zhang et al., 2016) (see Table 4.3). Since most of these studies model the adoption of PV or other technologies, "households" are most common decision-makers in this regard. Majority of these models limit their agent population to the households that live in a single-family building, because installation of renewable energy in other types of housing (rented apartments, multi-family housing) is subject to additional legal or physical constraints. However, few models are exceptions: Mittal et al. (2019b) and Mittal et al. (2019a) differentiate agents into tenants and house owners, where only house owners can buy and install PV and tenants can choose from green electricity or community solar program; Nava-Guerrero et al. (2021) attempts to represent group decision-making regarding heating system, insulation or RE system installation in multi-family houses. In other models, building (or building block) owner (Mehta et al., 2019; Preisler et al., 2017) and building agents (Lee and Hong, 2019) can make building-level decisions, i.e., adopting PV or renovation. The rationale of these models is that there is only one building owner that can make such a decision.

While the above-mentioned studies focus predominantly on one type of stakeholder, there are few models that involve different types of stakeholders as

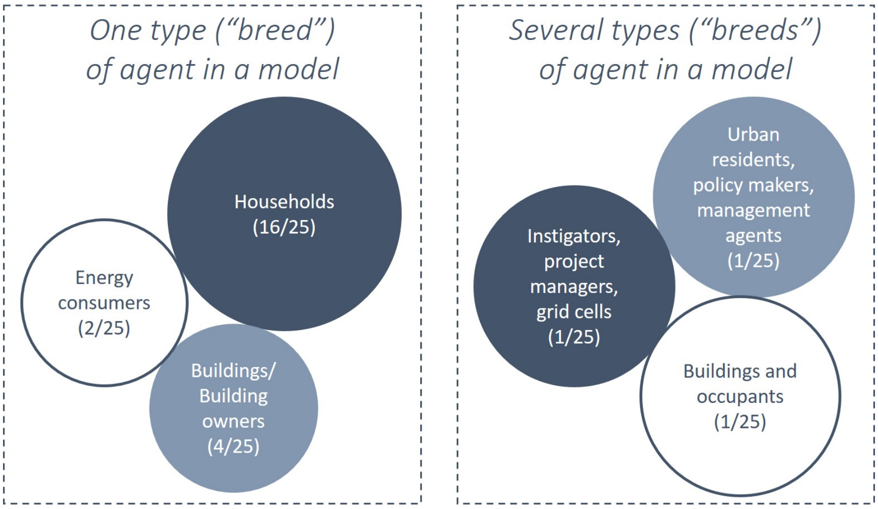

Figure 4.4.: Agent types

agents (Busch et al., 2017). For example, in Busch et al. (2017), instigator agents (i.e., local authorities, commercial, and community-based developers) are driving the development of projects, whereas "projects" are management agents responsible for carrying out actions on behalf of their parent instigators (Busch et al., 2017). In models with multiple types of stakeholders, it is becoming more challenging to draw a line between agents and other entities, e.g., as in Azar and Al Ansari (2017), as all of them are essentially realised as classes. However, one can observe the tendency to call human-like entities "agents", e.g., instigator agents, and passive entities like grid cells and projects as "entities" (Busch et al., 2017). Figure 4.4 summarises the types of agents I identified in the reviewed models.

The essential part of ABMs is decision rules that govern the actions of agents. Decision rules are realised with the help of attributes that describe agents (Dam et al., 2013). Moreover, interaction and social influence play a significant role in agent's decision-making. Hence, the following subsections give an overview of the decision-making rules and agent interaction strategies implemented in the reviewed models.

4.3.3. Agent Decision Rules

Decision-making rules (also called behavioural rules, decision rules or models, or just "rules") are methods by which agents' dynamic states can change their value and translate into agent action (Dam et al., 2013). Behaviour is the overall sum of agent actions and state changes (Dam et al., 2013). However, authors often use the terms "actions", "behaviours" and "decisions" interchangeably (An, 2012). The ODD protocol suggests to include a detailed description of individual decision-making (Müller et al., 2013). The information such as identifying subjects and objects, the method, the uncertainty, and other aspects must be part of this documentation (Müller et al., 2013). However, in practice, such protocols are rarely adhered to by the authors.

The articles describing the diffusion ABMs are more explicit about the decision-making algorithms. In such models, agents decide to adopt or not adopt (i.e., to invest or not invest in a certain technology or to perform a certain energy-related action) based on specific rules or algorithms. Decision rules range from simple ad-hoc rules to most elaborate models, such as psychosocial or cognitive models (Dam et al., 2013). The classification of existing decision models has been previously done by An (2012) for human agents in ecological ABMs, by Kiesling et al. (2012) and Zhang and Vorobeychik (2019) for agents in ABMs innovation diffusion and by Dam et al. (2013) for ABMs of socio-technical systems. The ODD+D by Müller et al. (2013) clusters agent decision algorithms based on the nature of the underlying assumptions:

- theory-based (e.g., microeconomic and psychosocial models)
- empirical-based (e.g., statistical regression models, heuristic rules),
- ad-hoc rules (i.e., dummy rules and pure assumptions that are not based on theories or observations),
- combinations of the above methods (see Figure 4.5).

Most of the diffusion ABMs cited in this chapter apply theory-based decision models, namely, psychosocial (also called "socio-psychological" or "cognitive") and microeconomic models. Psychosocial models are based on social psychology theories that assume that human decisions are based on psycho-

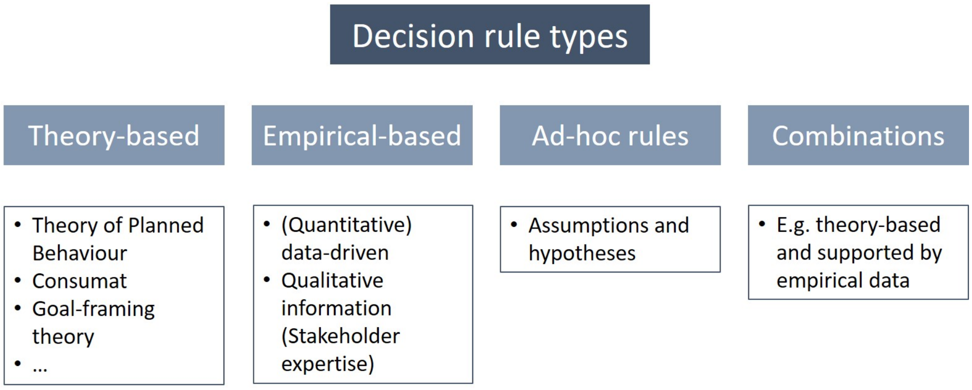

Figure 4.5.: Agent decision-making

logical rules, rather than on rational economic rules. The most frequently used psychosocial theory in the selected models is the Theory of Planned Behaviour (TPB) by Ajzen (1991). It states that human behaviour results from the intention to perform the behaviour; individual attitudes, subjective norms, and perceived expectations can influence the agent to perform such behaviour (Ajzen, 2002). Usually, the more favourable these three aspects of human psychology are, the stronger is the person's intention to perform a certain behaviour (Ajzen, 2002). The standard form of TPB is static, i.e., it describes how these three components are translated into intention and action at a given time. The models by Jensen et al. (2016), Jensen and Chappin (2017), and Rai and Robinson (2015) are examples of implementing this theoretical model. Other psychosocial models including "consumat" model by Jager (2000) in Zhang et al. (2016), Norm Activation theory by Onwezen et al. (2013) in Niamir et al. (2020), the goal-framing theory by Lindenberg and Steg (2007) in Gotts and Polhill (2017), and Influence, Susceptibility, and Conformity Model by Duggins (2017) in Zarei and Maghrebi (2020a), are also used. Several models rely on models from microeconomic or network theories, namely on innovation diffusion models. Azar and Al Ansari (2017) draw on the opinion dynamics models by Deffuant et al. (2000), Hegselmann and Krause (2002), and Mobilia et al. (2007) to represent the effect of energy feedback interventions among building residents.

Another class of frequently used agent decision-making model is the empirical-based heuristic models. They are described as models "not built on any grounded theories" and "having the impression of being ad-hoc" (Zhang and Vorobeychik, 2019). Agents are often assigned rules derived from empirical data, and also model parameters are selected such that results match simulated output against a real-life observation (An, 2012; Zhang and Vorobeychik, 2019). They might not represent the process of agent decision-making very accurately or realistically, but have the advantage of being easy to implement and to interpret (Zhang and Vorobeychik, 2019). Heuristic decision rules can be implemented in various ways. Several modellers favour data-driven approaches, thus, implementing machine learning algorithms, such as logistic regression models (Lee and Hong, 2019) and artificial neural networks (Yue et al., 2020). In this approach, several sets of factors that can affect the adoption of PV or energy-saving behaviour, given that data about those factors are available, are tested. The more qualitative approach is followed by Fouladvand et al. (2020) and Busch et al. (2017), who created the decision rules relying on the stakeholder's expertise.

Some models rely on ad-hoc rules without any validated theory or empirical grounding. Huang et al. (2019) derives the agents' decision logic from relevant secondary literature and assumes that social influence plays a great role in deciding to adopt weatherisation of a dwelling. In this model, agents decide between adopting weatherisation with the Weatherization Assistance Program or without and it depends on several attributes, memory length about the energy costs, current satisfaction level and information level about the assistance program. Mittal et al. (2019a) developed a decision model similar to Rai and Robinson (2015), but do not apply the TPB. The agents assess the affordability of PV options (i.e., buy, loan, community PV) and the attitudinal factors in the corresponding submodels and make the adoption decision based on certain if-else type rules. The remaining studies are summarised in Table 4.4.

4.3.4. Agent Interaction

Emergent phenomena to be observed via ABM is the result of not only individual decision-making but also agent interactions (Bonabeau, 2002; MacAl and North, 2010). The behaviour of agents is often influenced by the infor-

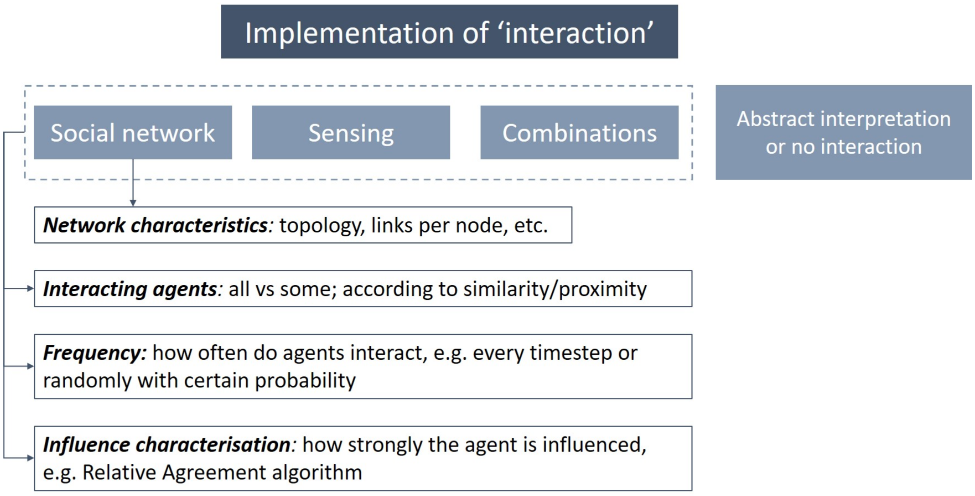

Figure 4.6.: Agent interactions

mation fed from its environment, including other agents. In the ODD the authors differentiate conceptually between "sensing" and "interaction": the first concept defines what state variables of which other individuals and entities can an agent perceive; the latter is the direct (via communication) or indirect (e.g., via a common resource) interaction between agents or between agents and other entities. However, in practice it is challenging to differentiate between those. For example, human agents' social influence (also known as "peer effect" or "neighbourhood effect") can be represented using either (or even both) of those concepts, as it seen from the pool of the reviewed papers. Hence, in this work, I consider "sensing" as one of the ways of representing interaction (as depicted in Figure 4.6).

In the selected studies, one must, first of all, differentiate between studies where agents can interact and influence each other and those where agents do not interact. Only two studies have not considered agent interactions in any way (Muaafa et al., 2017; Preisler et al., 2017). In Busch et al. (2017) and Yue et al. (2020), interactions are considered as important, however, treated in an abstract and implicit way. Table 4.4 shows how interactions are represented in each reviewed study.

The majority of studies which include agent interaction agents are often placed in a network structure, often called "social network", that imitates the relationship between agents, through which they can exert an influence upon each other based on certain rules (i.e., "peer influence" or "social influence"). The resulting structure allows modelling the social interactions of agents, resulting in the spread of desirable, or non-desirable, ideas, products, or behaviours (Mason et al., 2007; Newman, 2003) (also called "opinion dynamics"). One common way of doing so is through making an agent's decision dependent on other agents' (either selected group of agents or all agents) choice or decisions.

A social network typically consists of two components: individuals or agents (represented by nodes) and social connections (represented by edges or links). It can also have various topologies, e.g., small-world network, and created by various algorithms, e.g., Watts-Strogatz algorithm. Some modellers test the effect of varying the topology and other characteristics (e.g., number of links per node) of social networks (Azar and Al Ansari, 2017; Zarei and Maghrebi, 2020b; Zarei and Maghrebi, 2020a). A modeller should also specify between which agents interaction (or "sensing") occurs, between all agents or certain group of agents or between agents and other entities (e.g., grid cells). In a social network, usually, agents that have a link can interact or the influence of connected agents is more significant compared to those with whom the agent doesn't have one. This assumption is based on the empirical findings: friends and family have a larger impact on each other's behaviour than strangers (Jensen et al., 2016; Jensen and Chappin, 2017). In some cases, agents interact based on similarity (also called "homophily") (Mittal et al., 2019a) or geographical proximity ("neighbour effect") (Rai and Robinson, 2015).

Another choice that a modeller should take is regarding the frequency of interactions. Huang et al. (2019), for example, let agents that are linked with each other interact every time step, whereas "strangers" (without direct links) interact with a probability of 0.10. The "strength" of the influence can also be characterised in various ways. The most used is the opinion dynamics model by relative agreement algorithm, where agents with similar opinions have a stronger influence on each other than those whose opinions are more polarised (Deffuant et al., 2000). To sum up, there are usually four key things a modeller should consider when characterising an interaction of agents, as I summarise in Figure 4.6.

Table 4.4.: Agents, decision frameworks and representation of agent interaction.

Study	Agents	Decision Framework	Interaction
Azar and Al Ansari (2017)	occupants and buildings	*Theory-based*: several opinion dynamics models	Opinion dynamic models (information exchange within own social networks with following topologies: small world, scale free, and random)
Boumaiza et al. (2018)	households	*Theory-based*: linear threshold theory	Opinion dynamics; Barabási Albert model (scale free network)
Caprioli et al. (2020)	households	*Psychosocial*: TPB	Opinion dynamics; Watts-Strogatz small-world network
Jensen and Chappin (2017)	households	*Psychosocial*: TPB	Social influence changes the Subjective Norms (TPB); Watts-Strogatz small-world network
Jensen et al. (2016)	households	*Psychosocial*: TPB	Social influence changes the Subjective norms (TPB); Watts-Strogatz small-world network
Lee and Hong (2019)	buildings	*Empirical-based*: Logistic regression	'Sensing' in a geographic proximity (i.e., for every additional neighboring adopter in <100 m, buildings would be more likely to adopt PV)
Mehta et al. (2019)	building block owners	*Psychosocial*: TPB	Social influence changes the Subjective norms (TPB)
Mittal et al. (2019a)	households	*Ad-hoc rules*	'Visual interactions' (i.e., sensing) and information exchange based on similarity within own social networks (Watts-Strogatz small-world network)
Mittal et al. (2019b)	households	*Ad-hoc rules*	Interaction within and outside of fixed social networks with a probability
Muaafa et al. (2017)	building owners/buildings	*Ad-hoc rules*	None
Niamir et al. (2020)	energy consumers	*Psychosocial*: Norm Activation Theory	Simple opinion dynamics model in a fixed social network
Rai and Robinson (2015)	households	*Psychosocial*: TPB	Opinion dynamics via Relative Agreement (RA) algorithm; Small World network; interaction based on geographic proximity

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Table 4.4.: *Continued from previous page*

Study	Agents	Decision Framework	Interaction
Ramshani et al. (2020)	households	*Psychosocial*: TPB	Opinion dynamics via RA algorithm; Small World network; interaction in local (based on the physical distance) and global networks
Schiera et al. (2019)	households	*Psychosocial*: TPB	Opinion dynamics via RA; Small World network; interaction based on similarity
Zhang et al. (2016)	energy consumers	*Psychosocial*: Consumat	Opinion dynamics; Small world network
Busch et al. (2017)	instigators, projects and grid cells	*Empirical-based*: stakeholder expertise	Abstract interpretation of 'interaction'
Fouladvand et al. (2020)	households	*Empirical-based*: stakeholder expertise	Opinion dynamics in a small-world social network
Gotts and Polhill (2017)	households	*Psychosocial*: Goal-framing theory	Interaction based on similarity in a social network (no further details).
Huang et al. (2019)	households	*Ad-hoc rules*	Barabási Albert model (scale free network)
Nava Guerrero et al. (2019)	households	*Ad-hoc rules*	'Sensing' of group-decisions in the neighbourhood
Nava-Guerrero et al. (2021)	households	*Ad-hoc rules*	'Sensing' of group-decisions in the neighbourhood
Preisler et al. (2017)	building owners	*Ad-hoc rules*	None
Yue et al. (2020)	urban residents, policy-makers, management agents	*Empirical-based*: artificial neural networks	Abstract interpretation of 'interaction'
Zarei and Maghrebi (2020a)	households	*Theory-based*: Influence, Susceptibility, and Conformity Model	Opinion dynamics, social network: Random, Small-world, Scale-free

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Table 4.4.: *Continued from previous page*

Study	Agents	Decision Framework	Interaction
Zarei and Maghrebi (2020b)	households	*Theory-based*: Influence, Susceptibility, and Conformity Model	Opinion dynamics, social network: Random, Small-world, Scale-free

4.3.5. Technologies and Policies Modelled

This subsection discusses the technologies and policies that are in the scope of the reviewed ABMs. Similar to Hesselink and Chappin (2019), I identify which technologies and policies are explored using ABM. However, since the selected studies are not narrowed down to studies of technology diffusion only, it gives a broader overview of the discussion subject.

4.3.5.1. Technologies

From the 25 reviewed models, technologies are relevant to 20, while the rest have not modelled technology explicitly. Within these 20 studies, PV system, and specifically, diffusion of PV is the most frequently explored topic, as there are ten studies which focus on that (see Table 4.5). Majority of these studies consider the diffusion of a single technology: rooftop PV (Boumaiza et al., 2018; Lee and Hong, 2019; Mehta et al., 2019; Muaafa et al., 2017; Schiera et al., 2019), feedback device (CO_2 meter) (Jensen et al., 2016; Jensen and Chappin, 2017). In some cases, there could be several options are available for agents: Mittal et al. (2019a) and Mittal et al. (2019b) let agents choose between buying PV via cash payment of a loan, adopting community solar (i.e., renewable energy community) or opting for green electricity; Ramshani et al. (2020) make agents choose the optimal solution for their rooftops – either rooftop PV or green roof; Nava-Guerrero et al. (2021) introduces the combinations of technologies as “technology state” of a household (i.e., combination of heating system, insulation level, and appliances). Building insulation or renovation is addressed in these three studies: Huang et al. (2019), Nava Guerrero et al. (2019), and Preisler et al. (2017). Most studies are interested in the adoption of technologies by households: under what conditions are households willing to adopt these technologies, how does it affect their subsequent energy consumption, etc. Zhang et al. (2016) call the latter "learning" and observes how the installation and the subsequent interaction with this technology make them decrease their energy consumption.

Finally, the five studies focus on the energy-related behaviour that is not directly linked to a single technology. For example, the works by Azar and Al Ansari (2017), Zarei and Maghrebi (2020b), Zarei and Maghrebi (2020a), and Yue et al. (2020) investigate how feedback interventions could be improved, so that building occupants consume even less energy. Although the consumption of energy practically occurs as a result of interaction with certain technology (e.g., heater, shower, computer), such details are ignored in these models in order to focus on the macro-level phenomena, such as the interaction of occupants in their network (Azar and Al Ansari, 2017). Similarly, Niamir et al. (2020) examined the effect of several actions (i.e., investment, conservation, switching) in different socio-political framework conditions without emphasising the technological aspects. For a more detailed description of the review articles regarding ABMs refer to Table 4.1.

4.3.5.2. Policies

The selected 25 works can be the first split into those that explicitly model policy interventions (11) and those that do not (14). The policies covered in the 11 models are of two major types: ones that promote investment for energy-efficient technology (PV, DH, feedback device, etc.) and those that encourage energy-saving behaviour. The examples of the first type of policies are those that stimulate PV system investments (Mehta et al., 2019; Rai and Robinson, 2015; Ramshani et al., 2020; Schiera et al., 2019), assistance programs for weather-proofing (Huang et al., 2019), and promotional campaigns for feedback devices (Jensen and Chappin, 2017). The examples of the interventions for stimulating energy-saving are energy feedback mechanisms (Azar and Al Ansari, 2017). Beyond these clusters, Niamir et al. (2020) introduces several carbon emission price scenarios to see how it affects the emissions caused by household energy consumption. Busch et al. (2017) explore various ways of encouraging different district heating (DH) system developers and found out that creating policy specific to the motivations and capabilities of different actors, enabling networking and learning, and supporting all stages of the decision process is crucial for developing DH network successfully.

The prevailing share of the papers do no implement policies explicitly. They rather explore various socio-economic or other aspects that can affect the policy design or help policymakers make decisions or interpret the results of their model for policy-making (Zhang et al., 2016). For example, Nava Guerrero et al. (2019) investigates the socioeconomic conditions, such as value orientation of the population, gas price changes, the time horizon for investment evaluation, that support the transition to the natural gas-free economy.

The detailed description of how policies are implemented in the models are provided in Table 4.5.

Table 4.5.: Technologies and policy scenarios modelled using ABM.

Study	Technologies	Decision Regarding Technology	(Policy) Scenarios
Azar and Al Ansari (2017)	No technology	Energy-saving in buildings	No policy; insights for energy feedback methods, for any building stock
Boumaiza et al. (2018)	PV	Adoption	No policy
Caprioli et al. (2020)	PV	Adoption	Subsidies for low-income and high-income classes; a discount voucher proposed by PV sellers; an information campaigns on environmental issues & on adopting PV
Jensen and Chappin (2017)	Feedback device (i.e., CO2-meter)	Adoption and resulting energy-efficient heating behavior	Promotion-type policies (i.e., marketing strategies) to support product diffusion: giving away, lending out and raising awareness about CO2-meter/feedback device

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Table 4.5.: *Continued from previous page*

Study	Technologies	Decision Regarding Technology	(Policy) Scenarios
Jensen et al. (2016)	Feedback device (i.e., CO2-meter)	Adoption and resulting energy-efficient heating behavior	No policy; incentives and financial supports for PV systems are included in economic factors
Lee and Hong (2019)	PV	Adoption	No policy
Mehta et al. (2019)	PV	Adoption	"Self-consumption Communities": building owners can install PV and sell the electricity to their tenants at prices lower than the retail price of electricity
Mittal et al. (2019a)	PV	Adoption	No policy; different renewable energy models (e.g., solar community, buy/lease PV, etc) with different conditions (price, time, etc) for agents to adopt
Mittal et al. (2019b)	PV	Adoption	No policy; different renewable energy models (e.g., solar community, buy/lease PV, etc) with different conditions (price, time, etc) for agents to adopt
Muaafa et al. (2017)	PV	Adoption	No policy
Niamir et al. (2020)	PV	Adoption	Carbon price as a climate policy scenario
Rai and Robinson (2015)	PV	Adoption	Rebates for low-income households (i.e., households in the bottom quartile of wealth, proxied by home value)
Ramshani et al. (2020)	PV, green roof	Adoption	Investment Tax Credit, promotional campaigns
Schiera et al. (2019)	PV	Adoption	Self-consumption scheme (PV electricity is sold at market price) and Citizen/Renewable Energy Community scheme (share the electricity produced by a single PV unit with many citizens, e.g., in a condominium)

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Table 4.5.: *Continued from previous page*

Study	**Technologies**	**Decision Regarding Technology**	**(Policy) Scenarios**
Zhang et al. (2016)	Smart meter	Learning after SM adoption, energy-saving behaviour	No policy; insights for facilitation of learning following the smart meter roll-out
Busch et al. (2017)	DH network	Project development	Forcing the Local Authorities to have a heat strategy; increasing the availability of capital finance for all DH project instigators; support community instigators, i.e., include proactive LA (Energy Leader) and support at every stage of the DH development
Fouladvand et al. (2020)	Renewable heating technology	Joining or exiting a TEC	No policy
Gotts and Polhill (2017)	Electric appliances, insulation	Purchase	No policy described, but the model is capable
Huang et al. (2019)	Weather-proofing ("weatherization" for winter) technology	Adoption	Publicly funded Weatherization Assistance Programs that are intended to help low-resource residents improve the energy efficiency of their homes
Nava Guerrero et al. (2019)	Insulation, renewable heating	Investments in new technology	No policy; changes in natural gas price and electricity price are taken as proxies for market forces and policies
Nava-Guerrero et al. (2021)	Insulation, renewable heating	Investments in new technology	Fiscal policy (i.e., linear growth of natural gas taxes, taxes on electricity, and regulated price of heat from networks) and disconnection from gas network
Preisler et al. (2017)	Renovation technology	Renovation decision	No policy
Yue et al. (2020)	No technology	Energy-saving behaviour	Range of external situational factors are tested: social norms related to energy saving, popularization of economic energy-saving policies, etc

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Table 4.5.: *Continued from previous page*

Study	Technologies	Decision Regarding Technology	(Policy) Scenarios
Zarei and Maghrebi (2020a)	No technology	Energy-saving behaviour	No policy; insights for normative interventions (ecofeedback programs)
Zarei and Maghrebi (2020b)	No technology	Energy-saving behaviour	No policy; insights for EEP

4.3.6. Spatial and Temporal Aspects

Identifying the spatial and temporal scale of the models is important in order to understand the system modelled. Moreover, certain patterns and processes can be dependent on the scale (Dabiri and Blaschke, 2019) and, thus, they need to be clearly stated. By spatial scale, "geographic scale" is meant, defined as a research area's spatial extent in a study (Dabiri and Blaschke, 2019). The geographic scale of the models considered range from "group of buildings" (Azar and Al Ansari, 2017) to an entire city, such as Hamburg (Preisler et al., 2017). 16 studies describe community, or district, or neighbourhood-scale models, while nine studies are in city-scale (Busch et al., 2017; Jensen and Chappin, 2017; Preisler et al., 2017; Rai and Robinson, 2015; Yue et al., 2020; Zhang et al., 2016). Although these articles present the models as having been applied to specific geographic scales (i.e., via case studies), it is difficult to say if they can be scaled up or down, as it might depend on many factors.

The chosen scale in ABM usually determines the number of entities (i.e., agents) covered (Mahmoud et al., 2020). This can be limited by computers' processing capacity, especially if decision algorithms are sophisticated, much data is used, or a considered city is very large, e.g., like in (Lee and Hong, 2019). Therefore, the majority of selected models opt for district or neighbourhood scale. Those whose models are in city-scale focus on smaller cities of about 100,000 -150,000 (Jensen et al., 2016; Jensen and Chappin, 2017;

Muaafa et al., 2017). Only one model has modelled a city of approx. 174,000 households and the simulation had to be carried out on a supercomputer (Rai and Robinson, 2015). There are also such models whose scale depend on the topic of research. For example, DH network development is usually city-scale phenomena (Busch et al., 2017), the development or properties of energy communities are explored on a neighbourhood or district level (Fouladvand et al., 2020; Mittal et al., 2019a).

Although traditionally ABMs have not focused on the geographic environment and spatial representation, more and more models are striving to represent space explicitly and realistically (e.g., using GIS techniques) (Manson et al., 2020). According to Manson et al. (2020), models can have three levels of spatial explicitness:

1. implicit and non-geographic representation of space (e.g., social networks that are only partially tied to space);
2. explicitly represented but abstract in how it maps onto reality (e.g., Schelling's segregation model);
3. explicit and realistic spatial representation. Among the reviewed models, only a few are spatially explicit and realistic.

For instance, Caprioli et al. (2020), Lee and Hong (2019), Rai and Robinson (2015), and Schiera et al. (2019) join building information with actual geographical locations of those buildings and have a clearly defined boundaries of the study area. The rest of the models integrate spatial properties in different, semi-abstract ways. For example, in Mittal et al. (2019a) and Mittal et al. (2019b) agents in the same community, i.e., neighbours, are defined by a community ID, and each agent in a community becomes aware when somebody in that community installs a PV.

The temporal scale is a duration of a process observed, i.e., time horizon between the start and end of a single simulation run. Temporal resolution represents the unit of a time step in a considered model. According to temporal scale and resolution, the reviewed studies have time horizons of several years and resolutions of one month or three month-periods. These models have large simulation horizons and resolutions because the behavioural dynamics captured in those models occur in lower temporal resolutions. For example, in real life, people's attitudes do not change in a matter of hours. Such time horizons and resolutions are characteristic of policy-guiding models, aiming to observe the effect of a policy intervention over the years. In their models, the authors Lee and Hong (2019) and Rai and Robinson (2015) choose the years when adoption data are available, which makes it possible to improve their empirical model in such a way that the simulated outputs fit the real adoption data.

4.3.7. Empirical Grounding

Empirical grounding of ABMs is becoming more important, especially for models that aim to reflect a specific real-world situation and provide decision support for policymakers and stakeholders (Smajgl and Barreteau, 2014; Zhang and Vorobeychik, 2019). As opposed to hypothetical or theoretical (or highly abstract) ABMs, empirical ABMs use real-life data to parameterise models, initialise simulations, and evaluate model validity (Zhang and Vorobeychik, 2019). Modellers try to improve the realism of agent decision-making algorithms by consulting with system-relevant actors (Busch et al., 2017; Fouladvand et al., 2020) or relying on empirical data (Lee and Hong, 2019; Jensen et al., 2016; Schiera et al., 2019), e.g., geospatial information on buildings. It is becoming more feasible due to the contemporary trends one can observe the availability of high-resolution data sets, the spread of open data culture in science, advances in data analytics, machine learning, and computational power. Therefore, it is aimed to assess for what purpose, what kind of, and how empirical data is used in the selected ABMs of district energy systems. Empirical data includes both qualitative and quantitative data based on observation or experiment.

The review by Hesselink and Chappin (2019) highlights that empirical data in ABMs are used for two general purposes:

1. to form the agent decision-making algorithm;
2. to determine the specific properties of technologies, policies, etc. that an agent can access to use in their decision rules.

In the first case, empirical data from surveys, statistical data (i.e., census), interviews, and other sources are used to determine the attributes (both which attributes and their values) of the agents that are further incorporated in a decision-making framework (as described in Section 4.3.3). Jensen et al. (2016) describe how they utilised empirical data for creating household agents and their social network in the appendix of their article. Building data (i.e., floor area, spatial information, etc.) are connected to agents, and the commercial geo-marketing data defines the "lifestyle" of agents, which further define their affinity for technology and behaviour adoption. Social influence is modelled by introducing a social network based on interviews with households. The second purpose of integrating empirical data involves using statistical data and secondary literature to define other, for example, scenario-relevant information or model parameters (i.e., global parameters). For example, Azar and Al Ansari (2017) use building energy consumption survey data to initialise the model-level parameter "building energy intensity" and the number of agents in each building. However, it is not easy to determine for all models for what the specific data is used, as authors do not sufficiently describe it. Sometimes the authors refer to another article for detailed information about surveys or stakeholder interviews (Busch et al., 2017; Gotts and Polhill, 2017).

In general, there are three processes in model building where the use of empirical data make models more reliable and realistic: parametrisation, calibration and validation (Castro et al., 2020). The parameterisation is the process of connecting model and target system (i.e., the real system being modelled) via assigning the set of parameters and their values to enable simulation (Smajgl and Barreteau, 2014). In line with observations of (Castro et al., 2020), only a few modellers explicitly differentiate their modelling process into these three phases. Moreover, if calibration and validation are somewhat known to data-driven modellers, the process of parameterisation is not recognised as much. Among the selected models, only Jensen et al. (2016) and Jensen and Chappin (2017) describe parameterisation in more detail: they select the parameter values to reflect the empirical patterns of ventilation behaviour adoption derived from survey data.

Calibration is the adjustment of parameters to ensure that model output matches the relevant empirical data, e.g., in a specific location and application (Castro et al., 2020). The difference to validation is that the parameters are tuned to match a specific context (i.e., location, time), which does not necessarily mean that the model will exhibit accurate results and be predictive upon application in another context. To achieve that it has to be first validated on a separate set of data independent of data used for calibration (Zhang and Vorobeychik, 2019). The following models describe how they calibrated their models: Muaafa et al. (2017) calibrates the parameters of the logistic function governing the adoption of PV based on the secondary literature and publicly available data; Ramshani et al. (2020) performs the partial calibration (i.e., only of the financial submodel) based on the values reported in the literature, experts' opinions and publicly available datasets; Jensen et al. (2016) provides an indirect calibration with three empirical patterns, the same used for parameterisation in Jensen and Chappin (2017). As for the remaining models, some do not differentiate between validation and calibration (Mehta et al., 2019), some call calibration "model fitting" (Rai and Robinson, 2015), but the majority do not mention calibration at all. Often authors mention the lack of data for calibration as their limitations (Busch et al., 2017; Ramshani et al., 2020).

Validation aims to achieve the matching between the observations of the models and reality. It should not be confused with "verification", which is the process of making sure the model implementation is carried out correctly with respect to the conceptual model (Hartley and Starr, 2010). As ABM is a highly multi-disciplinary and flexible framework, its validation is a highly debated topic. For more detail, it is suggested to refer to the works of Fagiolo et al. (2007) and Zhang and Vorobeychik (2019) that explore this topic in more detail. Our observations are mostly limited to the validation processes provided in the selected works, the majority of which either do not mention validation, state it as a limitation and future task, or have insufficient information on the validation.

Among the models which consider validation, there are two following generic approaches. The first approach is an aggregate behaviour validation, mainly based on statistical data fitting. Rai and Robinson (2015) and Lee and Hong (2019) applied this way of validation, because they had empirical data on the number of adopters in a given location, over a certain period. Lee and Hong (2019) use the Wald test (i.e., Wald Chi-squared test) which tests the significance of a set of independent variables in a statistical model. Rai and Robinson (2015) first calibrate the six model parameters by an iterative fitting via historical adoption data and then validate the model in terms of predictive accuracy, i.e., comparing predicted adoption with empirical adoption level for the period starting after the last date in the calibration dataset. Also, they carry out temporal, spatial, and demographic validation (Rai and Robinson, 2015). Another group of modellers, i.e. Azar and Al Ansari (2017), Busch et al. (2017), and Zarei and Maghrebi (2020a), pay more attention to the validation of social processes and, by drawing on the work of Yilmaz (2006), offer conceptual, operational or structural, and technical validation (by this, Azar and Al Ansari (2017) refer to verification). Conceptual validation is the process of determining that the theories and assumptions underlying the conceptual model are correct (Yilmaz, 2006) and usually achieved by basing the model on validated concepts (Azar and Al Ansari, 2017; Zarei and Maghrebi, 2020a) or the insights from stakeholder workshops (Busch et al., 2017).

4.4. Discussion and Conclusions

This chapter reviews the state-of-the-art ABM approaches in the context of urban energy systems. By analysing a pool of 25 carefully selected research articles, one can observe some key domains where ABMs are used to simulate agent decisions and stakeholder behaviours in urban energy systems to guide policy design. The added value of this work is in the deep analysis of the preliminary work in agent-based modelling energy transition of district and neighbourhoods for the purpose of policy testing; understanding the key aspects of ABM for energy system modelling; and identifying gaps and future research streams.

In the district energy systems domain, the use of ABM for policy implications is becoming more prominent. The ability of ABMs to model complex interactions of independent agents enables the modellers to observe the broader implications of a specific policy design. The model structure, agent types, decision models, spatial and temporal scales are determined by the goals and the questions the ABM seeks to answer. Policy design studies are very versatile when it comes to specific purposes: from evaluating particular measures that stimulate the adoption of technologies, over studying the effect of social connectedness of households, to exploring novel concepts, such as the formation of TECs. It is important to reiterate that the origin of ABMs was in social and natural sciences. When ABMs become popular in other scientific fields, such as energy systems research, scientists try to adapt the original ABM concepts to fit their specific purposes. Such adaptations are often study-specific, and therefore, some essential modelling details may get lost or unclear to the audience without careful and standardised documentation. In this regard, the ODD protocol provides an essential standardised framework for model documentation.

Our analysis shows tremendous potential in ABMs to help policymakers make better policy decisions, especially in the upcoming years of post-covid recovery. With the Next Generation EU plan that pays a great attention to fair climate transition and funding research that supports such just transition, there's a chance to accelerate local neighbourhoods' and districts' decarbonisation. This is when agent-based models can help a great deal and be used to test various "what-if" scenarios.

The main challenge for future ABM applications in district energy systems is whether the ABM concepts can evolve and scale-up to represent the complexity of agents' decisions and interactions in a smart and decentralised energy system. Prosumers, i.e., those who self-consume PV energy and sell the surplus contribute vastly to energy transition (especially in countries with higher influx of solar energy) (Colasante et al., 2022). There are still many gaps and potentials in studying how to encourage the transition of consumers towards prosumers. ABM is useful in this regard, as it can represent different needs and interests of heterogeneous prosumers. That is something that no other modelling paradigm can offer.

Most of the reviewed ABMs deal with the various questions around adopting energy-efficient or renewable energy technology. These adoption decisions represent single-step investment decisions dependent on one decision-maker. However, there is a vast field of opportunity when it comes to exploring phenomena that involve multi-level decision-making and interactions of various stakeholders. Building stock retrofitting and development of district heating system are examples of such phenomena. Though a few exploratory ABMs investigate these topics, there are no models that comprehensively study retrofitting decision-making. The decision-making process and stakeholders will be different depending on whether social housing (Oliveira et al., 2021) or owner-occupied or rental sectors are studied. These differences in decision-making of owner-occupiers, landlords or housing associations, their implications and how to use them to tailor policies should be investigated further too. Furthermore, the studied literature mainly deals with the energy issues of residential neighbourhoods and not commercial or industrial entities. Therefore, it is exciting to look into whether ABMs, with their unique abilities, can answer some of the challenging energy transition questions related to commercial and industrial stakeholders.

Empirical data can be used to parameterise agent decision-making and provide contextual information to the model. Based on our analysis, significant gaps in the use of empirical data are found. Only a handful of reviewed models have made an explicit effort to clearly describe the use of data for parameterisation, calibration, validation, and verification purposes. Agent and model level parameter selection is often not given the due respect and attention it deserves. As the energy system complexity and, hence, the model complexity increase, careful parameterisation can significantly lower the computational cost. Lastly, careful integration of empirical data for model calibration, validation, and verification purposes significantly improves our confidence in the model and the results for practical purposes.

5. Agent-based modelling of building retrofit adoption in neighborhoods

5.1. Overview

This chapter introduces an ABM designed to simulate homeowners' decision-making processes in adopting energy-efficient retrofit packages, such as insulation measures and heat pumps, in the context of energy prices and policy interventions. First, how varying electricity and gas prices impact retrofit adoption is examined. Following this, the effect of three policy instruments currently implemented in the Netherlands is explored: heat pump subsidy, insulation subsidy based on specific measures and a ban on gas boilers starting in 2026 (see Section 5.3.2). By modeling these scenarios, it is aimed to understand how different policies—both individually and in combination—influence the adoption of retrofits.

The model examines two distinct decision-making frameworks: techno-economic and socio-psychological. These two approaches are analysed separately to understand how different factors influence retrofit adoption under each framework. The techno-economic model focuses on financial considerations, evaluating retrofits based on cost-effectiveness metrics such as Net Present Value (NPV). This model assumes that homeowners choose to retrofit when their current heating system reaches the end of its lifecycle. In contrast, the socio-psychological model incorporates the Theory of Planned Behaviour (TPB) (Ajzen, 1991), accounting for homeowners' attitudes, social norms, and PBC. Decisions in this model are influenced not only by economic and rational factors but also by individual attitudes toward retrofitting, perceived control over the process, and the adoption behavior of others within the neighborhood.

Comparing these two decision-making strategies is essential for understanding the full range of factors that influence homeowners' retrofit choices. Financial incentives alone may not be sufficient to drive adoption, as homeowners are also influenced by social dynamics and personal perceptions. By comparing these two approaches, we can assess the limitations of purely financial strategies and highlight the need for policies that address both economic and behavioral barriers to increase retrofit adoption. This broader understanding is critical for designing more effective and comprehensive energy-efficiency policies.

The model is applied to a Dutch neighborhood, characterised by a high share of homeowners (about 70% (Eurostat, 2023b)) and widespread use of condensing gas boilers (Bent et al., 2023). The Dutch government's 2026 mandate for hybrid heat pumps provides a policy backdrop for the analysis (European Heat Pump Association, 2024a). By simulating the decisions of homeowners over a 20-year period, the model captures how retrofit choices evolve under both economic and socio-psychological influences.

The study is set within a neighborhood context, where social interactions and peer influence significantly impact retrofit adoption. Our previous research (Akhatova et al., 2022) found that neighborhood cohesion and satisfaction are positively correlated with adoption likelihood. Homeowners with a strong sense of belonging are more inclined to follow peers in adopting sustainable technologies. Visible retrofits, such as solar panels or upgraded insulation, act as social signals that encourage others to adopt similar measures (Graziano and Gillingham, 2015). The model simulates these interactions, capturing both social dynamics and financial considerations in decision-making.

This neighborhood-based approach is essential because policies—such as financial incentives or information campaigns—are often implemented at the community level. Understanding how economic and social factors interact within neighborhoods is key to designing effective policies that encourage retrofit adoption. The comparison between the two models provides valuable insights into how different decision-making logics influence the spread of energy-efficient technologies, highlighting the need for policies that address both financial and behavioral barriers.

The remainder of the chapter is structured as follows. Section 5.2 presents the methodology of the work, including the agent-based model narrative, assumptions and simulation parameters (Section 5.2.1) and the detailed description of the decision-making strategies (Section 5.2.2). Section 5.3 demonstrates the results of the agent-based simulations for the two agent decision algorithms. In Section 5.4 the obtained results are discussed. Through this study, the insights that can inform policy and program designs to effectively encourage retrofitting in residential buildings are provided.

5.2. Method

An agent-based model (ABM) simulates the actions and interactions of autonomous agents to assess their effects on the system as a whole (Gilbert and Troitzsch, 2005). Unlike other modeling techniques, ABM models each agent individually, providing a detailed view of agent behaviors and decision-making processes (Gilbert and Troitzsch, 2005; Bonabeau, 2002; Epstein and Axtell, 1996). Its flexibility is particularly beneficial in fields like energy transition planning and policy analysis, where diverse actors and behaviors significantly influence system evolution (MacAl and North, 2010; Hansen et al., 2019). By moving beyond the simplifying assumption of a representative agent, ABMs facilitate interdisciplinary research, capturing the nuances of complex systems and making them powerful tools for analysing dynamic, interconnected systems (Niamir et al., 2020).

In this model, each agent represents a homeowner of a single-family house (detached, semi-detached, or terraced) in a neighborhood. Initially, all agents own gas boilers of varying ages. Each year, agents decide whether to adopt a retrofit package that includes a new heating system and possibly insulation improvements. The simulation runs from 2024 to 2044, calculating the number of adopters, types of measures adopted, renovation costs, and energy demand reductions.

The agent-based model of retrofit uptake proposed in this chapter is a result of the following distinct tasks, which are explained in detail in Sections 5.2.1 and 5.2.2:

1. definition of buildings, retrofitting packages suitable for these buildings, their respective costs and energy demand data

2. definition of algorithms or rules by which a homeowner agent makes a decision about renovating own dwelling.

5.2.1. Buildings and retrofitting options in a neighbourhood (case study)

This section covers the buildings (Section 5.2.1.1), retrofitting packages (Section 5.2.1.2), and household energy prices (Section 5.2.1.3) in De Maten, Apeldoorn, Netherlands, chosen for its representative building types (terraced, semi-detached, and detached) from the 1960-85 construction period.

5.2.1.1. Existing buildings and their current state

Buildings in De Maten are categorised using TABULA typologies (Tabula, 2016) based on Dutch national example buildings (Rijksdienst voor Ondernemend Nederland (RVO), 2022; Cornelisee et al., 2021). These archetypes represent buildings from various construction years and include detached, semi-detached, and terraced houses (Alavirad et al., 2022). Energy demands for space heating vary by building type and construction period, with details provided in Table 5.1. Although there are a total of 11,000 dwellings in De Maten (Barzilay et al., 2021), only a small neighbourhood of 100 buildings are selected for modelling.

Table 5.1.: Selected building archetypes (Tabula, 2016)

Building type	Tabula name	Reference area $[m^2]$	Energy need for space heating $[kWh/m^2a]$
Detached 1965-1974	NL.N.SFH.02.Deta	158	217
Detached 1975-1991	NL.N.SFH.03.Deta	169	136
Semi-Detached 1965-1974	NL.N.SFH.02.Gen	135	181
Semi-Detached 1975-1991	NL.N.SFH.03.Gen	135	107
Terraced Between 1965-1974	NL.N.TH.02.Gen	117	148
Terraced Between 1975-1974	NL.N.TH.03.Gen	117	106
Terraced Corner 1965-1974	NL.N.TH.02.End	117	185
Terraced Corner 1975-1991	NL.N.TH.03.End	117	125

5.2.1.2. Retrofit packages

Retrofit packages include an electric heat pump (HP) or a condensing gas boiler (GB) and varying insulation levels (deep and moderate (Wahi et al., 2022)), based on Dutch regulations (see Table 5.2). Double-glazed windows (HR++) are also considered (AAglas, n.d.). Detailed description of retrofit packages are provided in Table A1.

Heating energy needs after retrofitting are calculated using the seasonal method per EN ISO 13790:2008. This method calculates the building energy need for space heating ($Q_{H,nd}$) by considering the heat transfer by transmission ($Q_{ht,tr}$) and ventilation ($Q_{ht,ve}$) of the building zone when heated (or cooled[1]) to a constant internal temperature and the contribution of internal ($Q_{gn,sol}$) and solar heat gains ($Q_{gn,int}$) to the building heat balance (Eq. 5.1). Many of the assumptions for this calculation, such as window orientation or heating days (i.e. 212 days) are adapted from Sunikka-Blank and Galvin (2013) which are available in Institut Wohnen und Umwelt (2016). The values of heating energy need after the renovation and the costs of these packages are provided in the Excel calculation tool, provided as a Supplementary material.

$$Q_{H,nd} = (Q_{ht,tr} + Q_{ve,tr}) - \theta_{h,gn}(Q_{gn,sol} + Q_{gn,int}) \tag{5.1}$$

[1]Cooling is not considered in this study

The assumptions regarding electric heat pump and gas boiler employed in retrofit packages are presented in the Appendix (Section A.2).

Table 5.2.: Description of the insulation levels

Insulation	Source	Min. U-values according to legal requirements	U-values applied in the model
moderate	RVO's exemplary (Rijksdienst voor Ondernemend Nederland (RVO), 2022)	$U_{roof} = 0.29$, $U_{wall} = 0.59$, $U_{floor} = 0.29$	$U_{roof} = 0.28$, $U_{wall} = 0.58$, $U_{floor} = 0.28$
deep	Building Decree 2012 major renovation (and new construction) (Cruchten, 2020)	$U_{roof} = 0.17$, $U_{wall} = 0.22$, $U_{floor} = 0.29$	$U_{roof} = 0.16$, $U_{wall} = 0.21$, $U_{floor} = 0.28$
double-glazing	RVO's exemplary (Rijksdienst voor Ondernemend Nederland (RVO), 2022)	$U_{window} = 1.40$	$U_{window} = 1.20$

5.2.1.3. Technology costs and energy prices

Retrofitting costs (excluding taxes) are based on German cost functions (Hinz and Hatteh, 2015) and adjusted to 2022 Dutch market conditions (Baukosteninformationszentrum Deutscher Architektenkammern (BKI), 2023; European Construction Costs (ECC), 2024). Household gas and electricity prices, given in real 2023 EUR/kWh. Three distinct scenarios are considered as summarised in Table 5.3; low electricity prices and high gas prices such as they could be observed in 2019, low electricity prices and high gas prices from 2022 and very high electricity and high gas prices from 2023.

Table 5.3.: Household electricity and gas prices in the Netherlands (Eurostat, 2024)

Base year	Household electricity prices (nominal) $[EUR/kWh]$	Household electricity prices (real) $[EUR_{2023}/kWh]$	Household gas prices (nominal) [EUR/kWh]	Household gas prices (real) $[EUR_{2023}/kWh]$
2019	0.206	0.245	0.094	0.112
2022	0.090	0.094	0.158	0.165
2023	0.475	0.475	0.248	0.248

5.2.2. Decision-making strategies for retrofit adoption

Agent adoption decision rules are crucial in ABMs, ranging from simple to sophisticated (Kiesling et al., 2012). Since decisions to invest in retrofit is argued to be a complex socio-technical process involving various factors and even different actors' influence (Wilson et al., 2015; Chersoni et al., 2022), the ABMs of energy-efficient retrofit adoption rarely opt for simple decision rules. Decision rules often follow existing theoretical frameworks stemming from social psychology, such as the Theory of Planned Behaviour (TPB) (Ajzen, 1991) or the Consumat (Jager, 2000). TPB is preferred often by modellers because of its flexibility and relative easiness to operationalise using the threshold value (Hesselink and Chappin, 2019). This model combines TPB and utility theory, inspired by models from Rai and Robinson (2015) and Moncada et al. (2021).

The decision process is multi-stage and consists of several stages:

1. Consideration: Identifying the need for retrofitting, triggered by heating system failure, end-of-life, or gas price hikes.

2. Decision: Deciding whether to retrofit.

3. Selection: Choosing a retrofit package.

Considering retrofitting occurs when there is a need to replace the current system, which can be triggered in three common cases: the current heating system breaks, the gas boiler reaches the end of its lifetime, or there is a sudden increase in gas prices. The first case is a "problem trigger", while the other cases are "opportunity triggers", as homeowners can choose to keep the old boiler (Hecher et al., 2017). These triggers are modelled using a Weibull distribution, assuming most condensing gas boilers last around 15 years (Plumbing Force, 2020; Vaillant, 2024; Viessmann UK, 2022). Once an agent's status is "considering", stages 2 and 3 follow. These stages are operationalised differently in the two decision frameworks. Table 5.4 summarises the main differences, with detailed explanations in Sections 5.2.2.1 and 5.2.2.2.

Table 5.4.: Operationalisation of the decision algorithms by stage

Decision stage	Techno-economical decision	Socio-psychological decision
1) Consideration	IF current (gas) boiler breaks	IF current (gas) boiler breaks ‖ it is near breakdown ‖ gas prices increase sharply
2) Decision	IF considering, then implement	IF an agent's intention to retrofit > threshold (according to the Theory of Planed Behavior) (see Section 5.2.2.2)
3) Selection	choose retrofitting package with max. Net Present Value (NPV)	retrofitting package with max. utility (see Section 5.2.2.2)

5.2.2.1. Techno-economic (or financial) decision-making ("FIN")

This decision-making model, referred to as "FIN", treats retrofitting as a financial decision triggered when the current heating system reaches its end of life. Homeowners, acting as financially-driven agents, adopt the retrofit package with the highest positive NPV. The process follows three stages, as shown in Table 5.4.

The differential NPV in Eq. 5.2 is the difference between the NPV of the considered retrofit package j and that of the standard gas boiler (gb) replacement (i.e. reference NPV) (Ancona et al., 2019). For each agent i, NPV_j^i and NPV_{gb}^i are calculated as in Equations 5.3 and 5.4 respectively.

$$\delta NPV_j{}^i = NPV_j^i - NPV_{gb}^i \tag{5.2}$$

$$NPV_j^i = -I_j^i + \sum_{t=0}^{n} \frac{-p_{j,t} \cdot Q_{use,j}/\eta_j}{(1+r)^t} + \frac{L}{(1+r)^t} \tag{5.3}$$

$$NPV_{gb}^i = -I_{gb}^i + \sum_{t=0}^{n} \frac{-p_{j,t} \cdot Q_0/\eta_{gb}}{(1+r)^t} \tag{5.4}$$

Where I_j and I_{ref} are the investments for retrofitting package j and gas boiler respectively; $Q_{use,j}$ is the annual useful energy after retrofit j; $p_{j,t}$ is the energy carrier's retail price at time step t; η_j is the heating system efficiency (gb stands for gas boiler); Q_0 is the annual useful energy before retrofit; and r is the discount rate. Insulation and glazing materials have a 30-year lifespan (Maia and Kranzl, 2019), while heat pumps and gas boilers last up to 20 years (Plumbing Force, 2020; Intuis, n.d.). The NPV analysis time frame is 20 years, assuming a residual value of 33% for insulation technologies.

5.2.2.2. Socio-psychological decision-making ("SOC")

This decision-making model, referred to as "SOC", integrates social and psychological factors, reflecting that human decision-making is deeply embedded in social contexts. It uses the TPB and includes peer influences. The process follows three stages described in Table 5.4. Figure 5.1 is the flowchart of the socio-psychological decision-making process implemented in the current ABM.

In Stage 1, an agent i considers retrofitting upon two triggers.

1. Approaching Breakdown: when T_{cons} years are left until the heating system's expected end of life ($t = T^i_{hs,l} - T_{cons}$). This indicates the system is losing efficiency or needs more maintenance. The old gas boiler's lifespan is modeled using a Weibull distribution[2]. Further details of this assumptions are in the Appendix (Section A.3).

2. Gas Price Increase: in case there is a sharp increase in gas price (compared to the previous year) sufficient to consider replacing the boiler. As Achtnicht and Madlener (2014) demonstrate, present and expected energy costs drive heating system replacements. Further details of this assumptions are in the Appendix (Section A.4).

In Stage 2, the decision to retrofit is based on the TPB, which projects and explains behavior under volitional control (Ajzen, 1991). TPB postulates

[2] Weibull distrubution is widely used to describe the lifetime distributions of systems (Bearda et al., 2018)

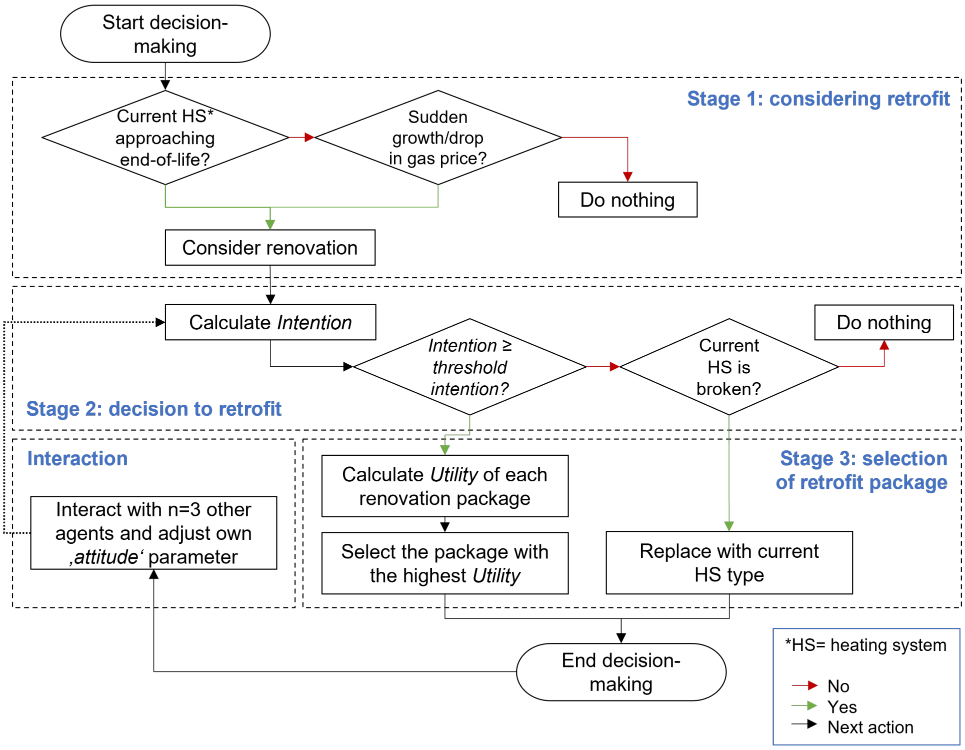


Figure 5.1.: Flowchart of socio-psychological (SOC) decision framework

that behaviors stem from intentions (Int), but can be hindered by factors like time, money, and knowledge. Widely used across various fields, TPB suits retrofit decisions, with empirical evidence linking intention to energy-efficient behavior (Ajzen, 2020; Chen and Gou, 2022; Conradie et al., 2023). As shown in Figure 5.2, an agent's decision to retrofit $D_i(t)$ depends on whether intention Int_i exceeds the threshold Int_{thr} (Eq. 5.5). Intention Int is calculated at each step for each agent i, while the intention threshold Int_{thr} is a calibrated constant (Section 5.2.3).

$$D_i(t) = \begin{cases} 1, & \text{if } Int_i^t > Int_{th,i} \\ 0, & \text{if otherwise} \end{cases} \tag{5.5}$$

The intention of agent i to retrofit is a function of attitude towards retrofitting

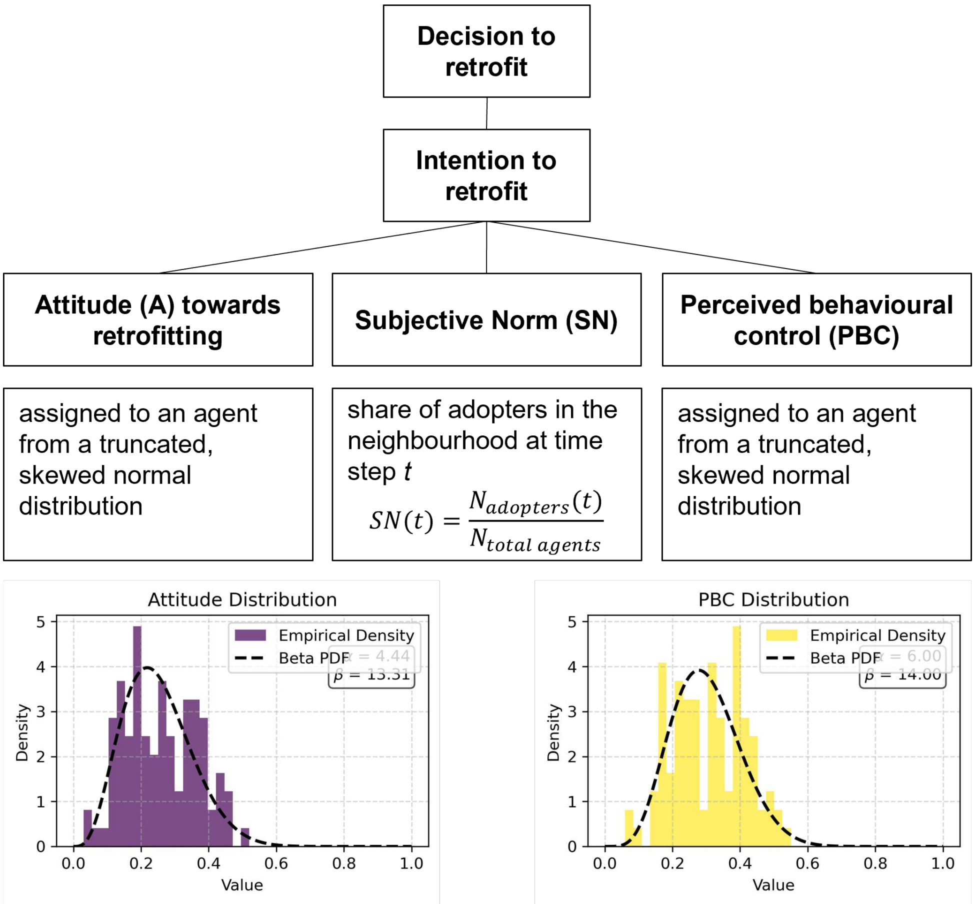


Figure 5.2.: Operationalisation of the Theory of Planned Behaviour in this ABM

$Att_i(t)$, "Subjective Norm", $SN_i(t)$ and "Perceived Behavioural Control", PBC_i. According to Conradie et al. (2023), these components significantly predict the intention to perform energy efficiency renovations. The relationship is expressed in Eq. 5.6, with weights [3] ($w_{Att,i}, w_{SN,i}, w_{PBC,i}$ summing to 1 (Eq. 5.7). The three components (Att, SN and PBC) are parameterised as demonstrated in Figure 5.2.

$$I_i = Att_i(t) * w_{Att,i} + SN_i(t) * w_{SN,i} + PBC_i * w_{PBC,i} \tag{5.6}$$

[3]The weights are based on the results of their relative impacts on the intention reported in Conradie et al., 2023.

$$w_{Att,i} + w_{SN,i} + w_{PBC,i} = 1 \tag{5.7}$$

Attitude toward the behaviour $Att_i \in [0,1]$ is the subjective probability that retrofitting will lead to positive outcomes, such as comfort, reduced energy bills, and lower CO_2 emissions (Wang et al., 2019; Kastner and Stern, 2015). It is initialised from a beta distribution and evolves over time through agent interactions. The parameterisation and evolution mechanism of attitude is described in the A.5.

Subjective Norm (SN) $SN_i \in [0,1]$ representing perceived social pressure, is conceptualised as the share of adopters in the neighborhood at time t (Eq. 5.8). It assumes each agent knows the number of adopters in the neighborhood, affecting all agents equally.

$$SN_i = \frac{N_{ad}}{N_{tot}} \tag{5.8}$$

Perceived Behavioral Control (PBC) $PBC_i \in [0,1]$ represents an agent's perceived power over their actions. Higher perceived renovation knowledge and income levels correlate with higher PBC (Conradie et al., 2023). PBC is initialised similarly to attitude but remains constant over time.

In Stage 3, the choice of a retrofit package is governed by utility theory. Agents rank packages by utility and adopt the one with the highest value. The utility U_j^i depends on the package j's normalised NPV difference $\widehat{NPV}_j$, complexity cx_j, and the product of energy-saving index es_j and the agent's attitude Att_i. The weights are equally distributed and sum to one, ensuring that utility calculation includes economic considerations, project complexity, and energy-saving potential. The utility equation is:

$$U_j^i = \widehat{NPV}_j \cdot w_{npv} + cx_j \cdot w_{cx} + Att_i \cdot es_j \cdot w_{es} \tag{5.9}$$

Complexity serves as an indicator of implementation difficulty and disturbance level, based on literature and expert knowledge (Klockner and Nayum, 2016; Stieß and Dunkelberg, 2013) (Table A3). The energy-saving index represents normalised[4] savings in final energy demand for space heating for each package.

5.2.3. Calibration of mean attitude, mean PBC and intention threshold

The socio-psychological decision-making model contains several uncertain parameters calibrated based on known adoption patterns in the Netherlands. Annually, over 400,000 gas boilers are replaced in residential homes (Bellini, 2021). The share of heat pumps among these replacements are estimated as summarised in Table 5.5. Heat pump adoptions in 2021 were used as a baseline, with a 57% increase in 2022 (European Heat Pump Association, 2023a) and partial data for 2023 (European Heat Pump Association, 2023b).

Table 5.5.: Estimation of heat pump (HP) share in yearly heating system replacement (European Heat Pump Association, 2023a; European Heat Pump Association, 2023b)

Year	Total HPs adopted	HPs in existing houses	HPs in heating system replacements [%]
2021	70,064	-	-
2022	110,000	40,000	over 10%
2023	162,235	91,226	over 23%

Note: *30,000 is estimated to be installed in Q4 ** 18,000 is estimated to be installed in Q4.

Based on the estimations presented in Table 5.5, we assume that between 10% and 23% of gas boilers will be replaced with heat pumps annually during 2022 and 2023. Using historical household energy prices from 2022 and 2023 and assuming subsidies for heat pumps and insulation, we simulate the share of retrofit packages that include heat pumps for these years. The share of packages with heat pumps (averaged across 2022 and 2023) for various combinations of mean PBC, intention threshold, and mean attitude is illustrated in Figure 5.3. The average of 10% and 23% – 16.5% – guided the

[4]min-max technique is used for normalisation

selection of parameter values resulting in a 16% share of heat pumps (see the selected parameters in Table A2).

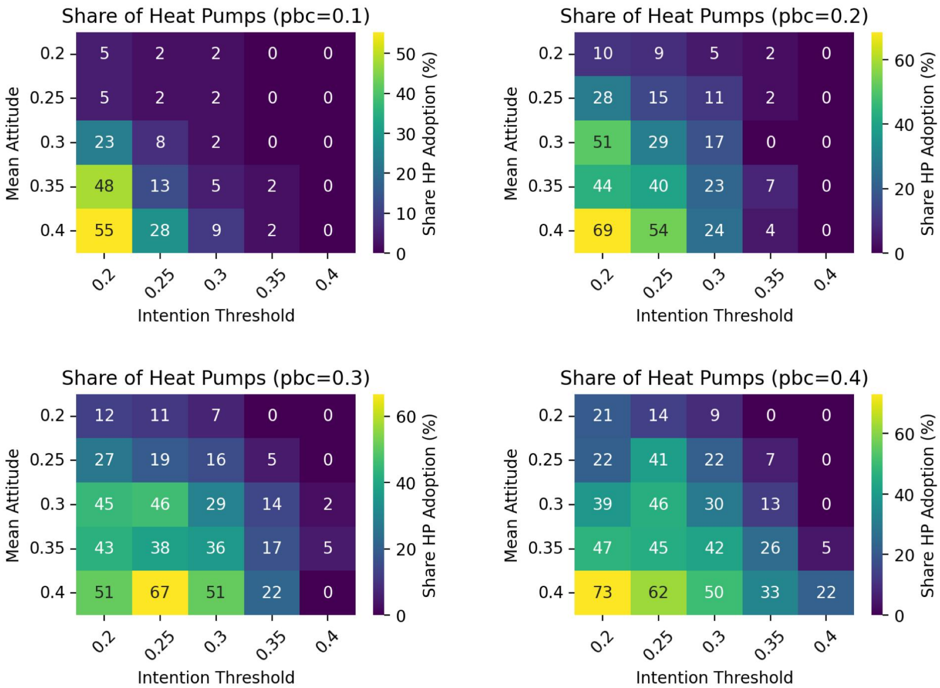


Figure 5.3.: Calibration results - share of heat pumps in annual heating system replacements (four graphs for four different values of mean PBC among agents)

5.3. Results

This section presents the results of three simulation experiments. First, the adoption of energy-efficient measures at different household electricity and gas prices are calculated (Section 5.3.1). Second, the impact of various policies on adoption rates are assessed (Section 5.3.2). Finally, a sensitivity analysis of key parameters is conducted (Section 5.3.3).

5.3.1. Adoption patterns under different electricity and gas price scenarios

The simulation results demonstrate varying adoption patterns of energy-efficient measures based on different electricity and gas price scenarios, described in Section 5.2.1.3. The adoption of retrofitting packages in the neighbourhood is illustrated in Figure 5.4, where the top row presents results for the techno-economic decision-making model (*FIN*) and the bottom row for the socio-psychological decision-making model (*SOC*).

As shown in Figure 5.4, under the *FIN, 2023* scenario (highest gas prices), a complete transition to heat pumps with insulation occurs by 2038. This shift is primarily driven by the significant cost savings associated with these packages. In contrast, the *FIN, 2022* scenario (lower electricity prices) results in a more diversified adoption pattern: approximately half of the agents choose heat pumps with insulation, while the other half opt for heat pumps without insulation. Even under the *FIN, 2019* scenario (lowest gas prices), heat pumps with insulation emerge as the most profitable option for half of the agents. The remaining agents either replace their gas boilers with new ones or combine this replacement with wall insulation. This suggests that while heat pumps are still considered a financially attractive option, the lower electricity prices make gas boilers a more viable choice for some. After 2038, the number of insulated gas boilers begins to decline. This shift occurs as the gas boilers initially adopted reach the end of their service life and require replacement. Since these agents have already invested in insulation, they do not need to reinsulate. Consequently, when their gas boilers reach the end of their service life, they select the most cost-effective replacement option available: another gas boiler without additional insulation.

The bottom row of Figure 5.4 illustrates the impact of socio-psychological factors on adoption decisions. Across all scenarios, a significant portion of agents opt to renew their existing gas boilers, reflecting a strong preference for the status quo. The *SOC, 2019* scenario, characterised by low gas prices, shows that over 80% of agents preferred to simply renew their boilers, with the remainder selecting one of the alternative options. In the other two scenarios, approximately 40% of agents choose heat pumps: in *SOC, 2022*,

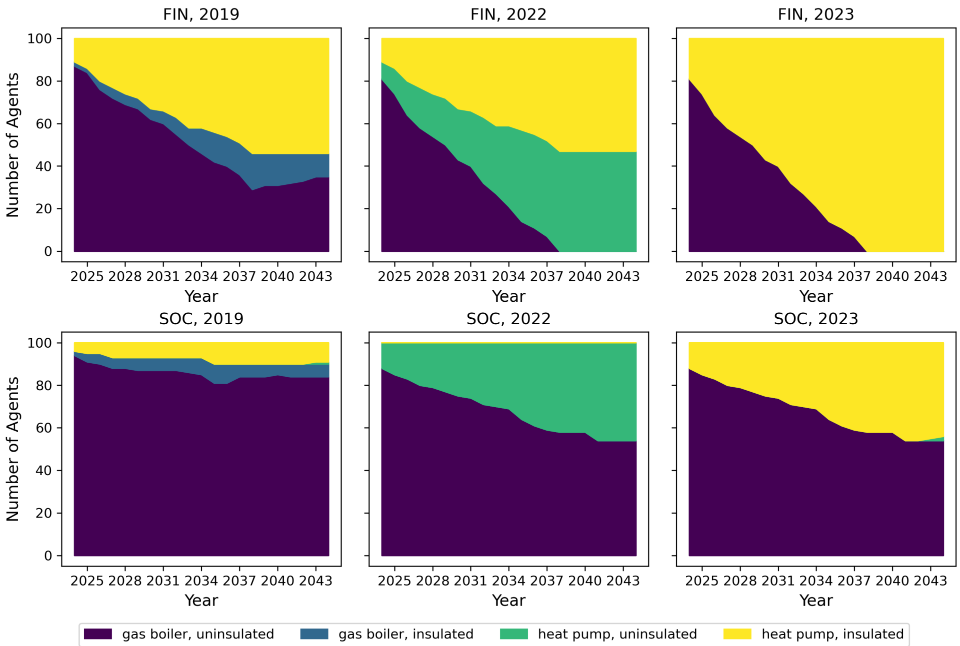


Figure 5.4.: Heating system and insulation state in the neighbourhood - reference scenario

these agents opt for heat pumps without insulation, likely due to low electricity prices, whereas in *SOC, 2023*, some agents initially choose heat pumps with insulation but later renew only the heat pumps, foregoing insulation.

This model demonstrates that, from a techno-economic perspective, insulating and installing heat pumps is generally more profitable than replacing gas boilers, depending on energy prices and house types. However, socio-psychological considerations reveal that homeowners tend to choose the familiar gas boiler over a more efficient yet less familiar alternative, unless they already have a strong intention to retrofit and other options than gas boilers have a higher utility rank. Nonetheless, energy prices play a significant role: lower gas prices encourage the renewal of gas boilers, while lower electricity prices promote the adoption of heat pumps.

Figure 5.5 presents the cumulative savings in final energy demand for space heating (*left*) and CO_2 emissions (*right*) resulting from the adoption of retrofit packages. The left panel demonstrates that financial decision-making consistently leads to greater savings in final energy demand compared to socio-psychological decision-making. This is primarily attributed to the more aggressive adoption of heat pumps with higher seasonal coefficients of performance (SCOPs) and deep insulation packages under financial decision-making. The *FIN, 2023* scenario achieves the highest savings, reaching a 90% reduction in initial neighbourhood final energy demand for space heating. In contrast, the *FIN, 2019* scenario, characterised by low gas prices, results in the lowest savings due to a slower transition to heat pumps and a higher prevalence of gas boilers with insulation. The right panel illustrates the corresponding CO_2 emissions reductions, which closely follow the trends observed in final energy demand savings. The *FIN, 2023* scenario again exhibits the most significant emissions reductions, while the FIN 2019 scenario demonstrates the least.

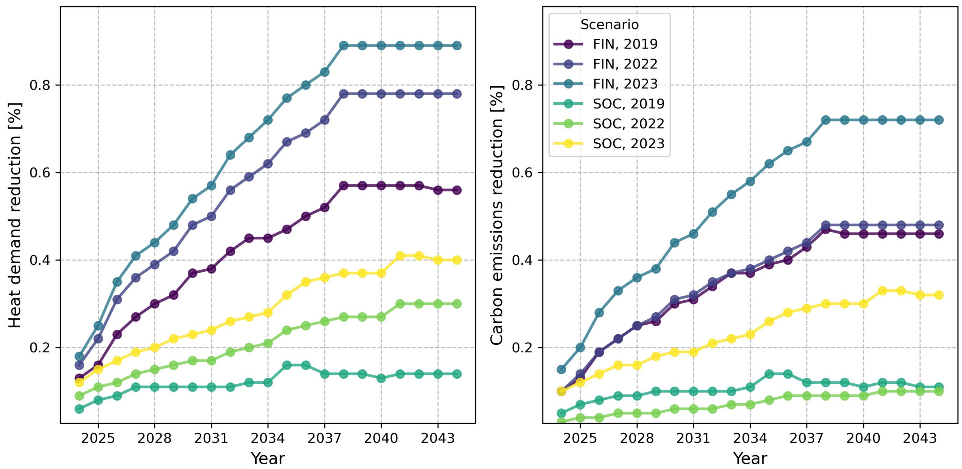


Figure 5.5.: Savings in final energy demand for space heating (left) and CO_2 emissions reduction (right)

5.3.2. Adoption patterns under various policy instruments

There is a number of policies in place in the Netherlands that aim to support sustainable home retrofit. Three distinct policy instruments implemented nationally are selected for the simulation runs:

1. heat pump subsidy covering 30% of the purchase price (Rijksdienst voor Ondernemend Nederland (RVO), 2024b)

2. insulation subsidy with the amount shown in Table 5.6 (Rijksdienst voor Ondernemend Nederland (RVO), 2024a)

3. ban on gas boilers starting from 2026 (Rijksoverheid, 2024)

The model assumes that all agents become aware of the subsidy existence.

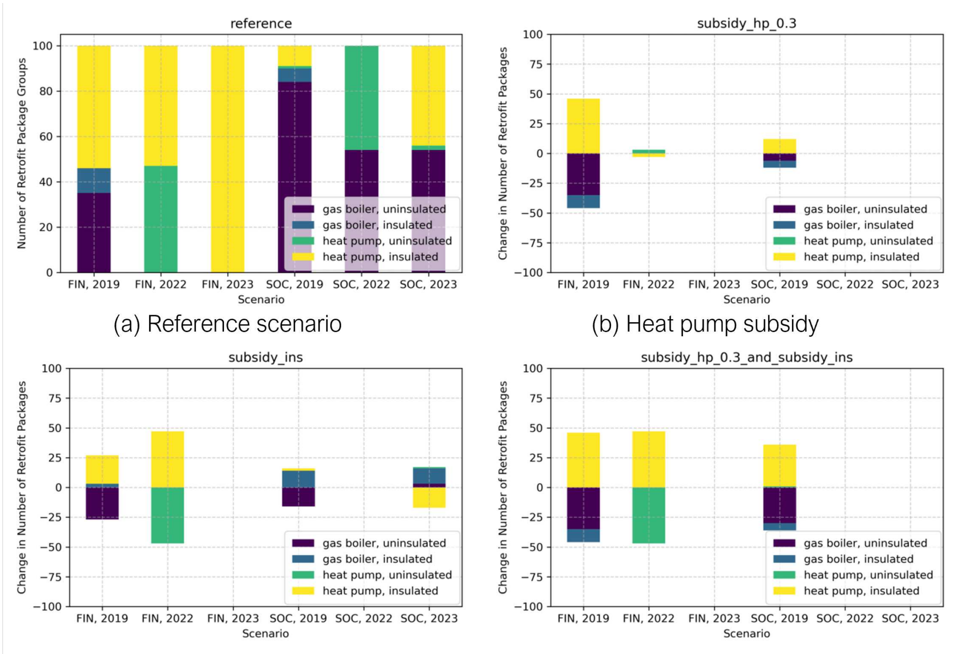
Table 5.6.: Subsidy amount for insulation measures of building components (Rijksdienst voor Ondernemend Nederland (RVO), 2024a). The subsidy values are for implementing two and more measure, the unit is in Euro per square meters of corresponding building element.

Component	Subsidy $[EUR/m^2]$
Facade	19
Roof	15
Floor (cellar)	3
Double glazing (windows)	23

Figure 5.6 shows the detailed breakdown of the final distribution of retrofit packages across different scenarios. *Panel* (a) illustrates the reference scenario, where the adoption of heat pumps with insulation is highest under the *FIN, 2023* scenario, followed by *FIN, 2022*. In contrast, gas boilers with insulation dominate the market in the *FIN, 2019* scenario. Panels (b), (c), and (d) will be described in Sections 5.3.2.1, 5.3.2.2 and 5.3.2.3 below, respectively.

5.3.2.1. Heat pump subsidy

Figure 5.6 (b) highlights the changes in the final mix of retrofit packages when heat pump subsidies are applied, as compared to the reference scenario in Figure 5.6 (a). In the *FIN, 2019* scenario, where gas prices are low, the introduction of heat pump subsidies makes heat pumps with insulation the most financially attractive options for most agents, leading to widespread adoption of these technologies.



(a) Reference scenario

(b) Heat pump subsidy

(c) Insulation subsidy

(d) Combined subsidies

Figure 5.6.: Retrofit package clusters at the end of the simulations for (a) Reference scenario; Change in retrofit packages adopted for (b) heat pump subsidy, (c) insulation subsidy and (d) combined subsidies, as compared to the reference case

In contrast, the *SOC, 2019* scenario shows only minimal impact from the subsidies, with just a few agents adopting heat pumps with insulation. This limited response reflects the strong influence of socio-psychological factors, where financial incentives alone are less effective in driving adoption. Similar patterns are observable in other scenarios, where changes from the reference scenario remain marginal.

Overall, the results suggest that while heat pump subsidies are effective in promoting adoption in the techno-economic decision framework, they do not significantly impact the adoption rate and retrofit package choices in the socio-psychological framework.

5.3.2.2. Insulation subsidy

Figure 5.6 (c) presents the changes in the final mix of retrofit packages when insulation subsidies are introduced, compared to the reference scenario in Figure 5.6 (a). Insulation subsidies encourage greater adoption of heat pump and insulation packages in both low gas and low electricity price scenarios of the *FIN* decision rationale. The most notable change occurs in the *FIN, 2022* scenario, where heat pumps with insulation become the most cost-effective option for all agents, leading to widespread adoption. In contrast, in the *FIN, 2019* scenario, only a portion of agents switch to heat pumps with insulation, while others continue to find gas boilers more financially viable.

By the *SOC* rationale, the impact of insulation subsidies is minimal. In *SOC, 2019*, insulation subsidies appear to incentivise approximately 20% of agents to implement insulation alongside renewing their gas boilers. In *SOC, 2023*, where high electricity prices and lower gas prices prevail, subsidies seem to make gas boilers with insulation more attractive than heat pumps with insulation. This is likely because the combination of high electricity costs and the high cost of insulation lowers the utility rank of heat pumps with insulation compared to gas boilers.

5.3.2.3. Combination of heat pump and insulation subsidies

Figure 5.6 (d) illustrates the changes in the final mix of adopted retrofit packages when both heat pump and insulation subsidies are applied, as compared to the reference scenario in Figure 5.6 (a). Similar to the results with insulation subsidies alone, this combined intervention prompts a full transition to heat pumps with insulation in scenarios with low gas prices (*FIN, 2019*) and low electricity prices (*FIN, 2022*).

In the *SOC* models, the combined subsidies influence only the scenario with low gas price conditions (*SOC, 2019*). In this case, they lead to a significant increase in heat pumps with insulation (over 30% above the reference scenario), demonstrating a stronger effect than each subsidy applied individually.

The minimal changes observed in *SOC, 2022* and *SOC, 2023* across all subsidy scenarios could be attributed to a limit on heat pump adoption, as determined by the calibration of social parameters to cap the share of heat pumps.

Overall, the subsidies are more effective in the *FIN* decision-making models across all pricing scenarios, driving a stronger shift towards energy-efficient technologies. In contrast, in the *SOC* decision-making models, the results suggest that subsidies alone are insufficient to significantly influence adoption among agents less inclined towards retrofitting. Hence, this analysis demonstrates that financial incentives alone are insufficient to overcome the social and psychological barriers that many agents face when considering energy-efficient retrofits.

5.3.2.4. Gas boiler ban

Figure 5.7 illustrates the adoption of heating systems and insulation over a 20-year period following the introduction of a gas boiler ban. Based on the *FIN, 2019* and *FIN, 2023* decision frameworks, heat pumps with insulation largely replace gas boilers as the most cost-effective option. In these scenarios, agents are financially motivated to adopt heat pumps with insulation to maximise energy savings. In contrast, under the *FIN, 2022* framework, where electricity prices are lower, agents predominantly adopt heat pumps without insulation. The lower electricity costs reduce the financial incentive to combine heat pumps with insulation, as the energy savings from insulation do not sufficiently outweigh its additional cost. Consequently, the adoption of heat pumps alone becomes the preferred option in *FIN, 2022*.

In the *SOC* framework, many agents adopt heat pumps without insulation. This behaviour occurs because, in the absence of gas boilers, agents who do not have a firm intention of renovating tend to choose the simplest option available—heat pumps—rather than undertaking more comprehensive retrofits, such as adding insulation. In *SOC, 2019* and *SOC, 2023*, approximately half of the agents adopt heat pumps without insulation, reflecting a mix of socio-psychological barriers and financial considerations. In contrast, in *SOC, 2022*, where electricity prices are lower, all agents opt for heat pumps without insulation, as the lower energy costs further diminish the perceived need for insulation. The lower the average attitude toward energy-efficient retrofits is in neighbourhoods, the smaller the share of households adopting insulation. As a result, the potential energy savings are not fully realised, leading to lower overall efficiency gains compared to scenarios where both heat pumps and insulation are widely adopted.

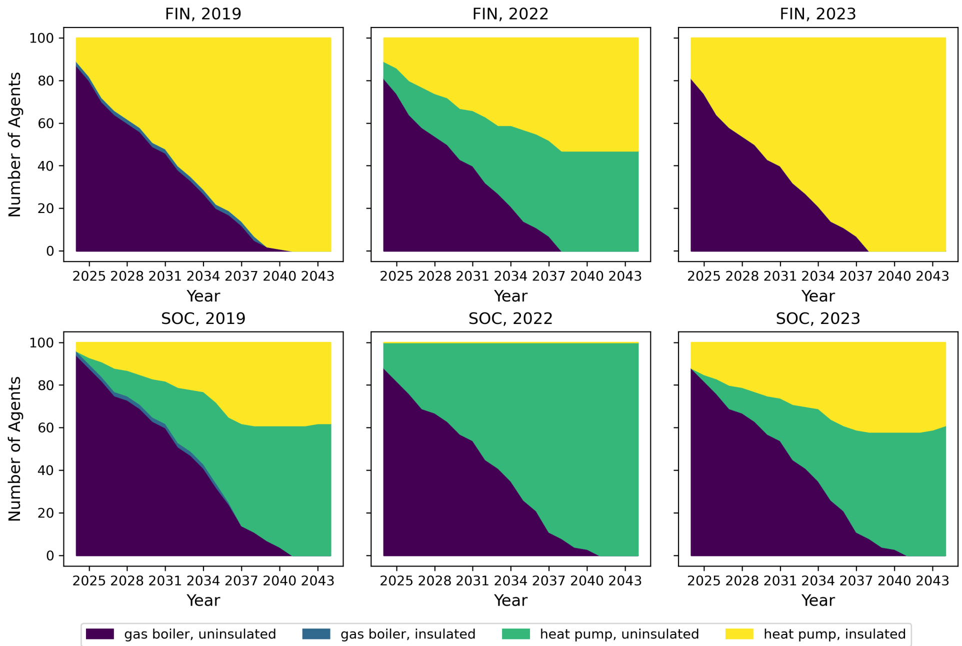


Figure 5.7.: Heating system and insulation state in the neighbourhood - gas boiler ban scenario

5.3.3. Sensitivity of the model to key parameters

Simulations are performed to examine the sensitivity of model results to various parameters, including heat pump and insulation costs, mean attitude, mean PBC, and intention threshold.

Figure 5.8 shows the share of heat pumps adopted with varying heat pump costs. In *FIN, 2019*, even a 25% decrease in heat pump costs leads to a 100%

adoption share of heat pumps. In *FIN, 2022*, low electricity costs make heat pumps consistently favourable, with their share remaining unaffected by higher investment costs. However, in *FIN, 2023*, where electricity prices are high, doubling heat pump investment costs results in an 80% drop in their share, as they become a less profitable option. Adoption behaviours in the *SOC* framework follow similar trends but are less sensitive to cost changes. For example, a 25% decrease in heat pump costs increases their share among adoptions by only 20%.

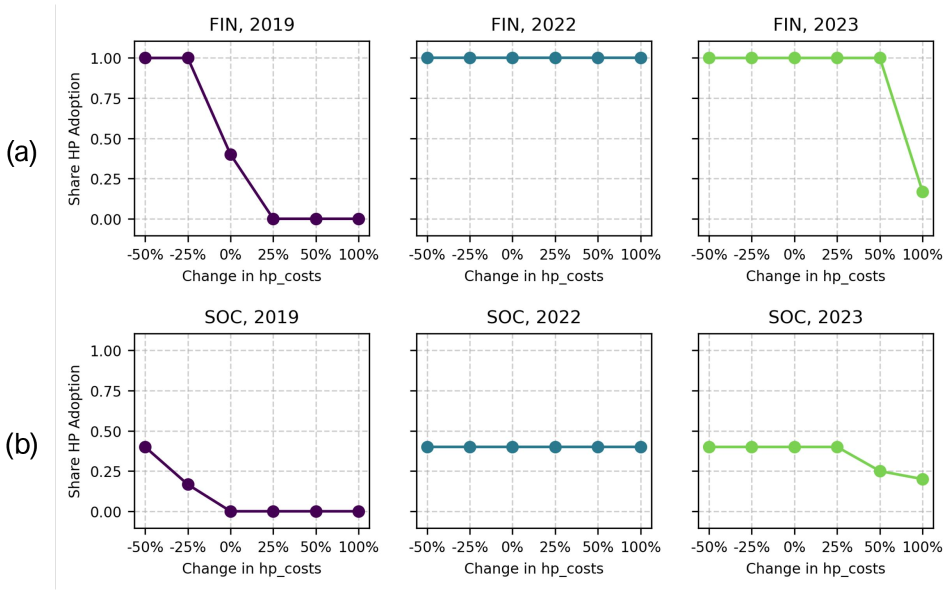


Figure 5.8.: Share of heat pumps adopted - sensitivity to heat pump costs

Figure 5.9 shows the final savings in final energy demand for space heating with varying insulation costs. In *FIN* scenarios, reduced insulation costs lead to higher energy savings, while increased costs result in lower savings. *FIN, 2019* is particularly sensitive, with doubled insulation costs eliminating savings entirely. In contrast, *SOC* scenarios follow similar trends but are much less sensitive to insulation cost fluctuations. An exception is *SOC, 2023*, where reduced insulation costs result in lower energy savings. This could occur because the utility rank of gas boilers with insulation surpasses that of heat pumps with insulation due to high electricity prices, which diminish the appeal of heat pump packages.

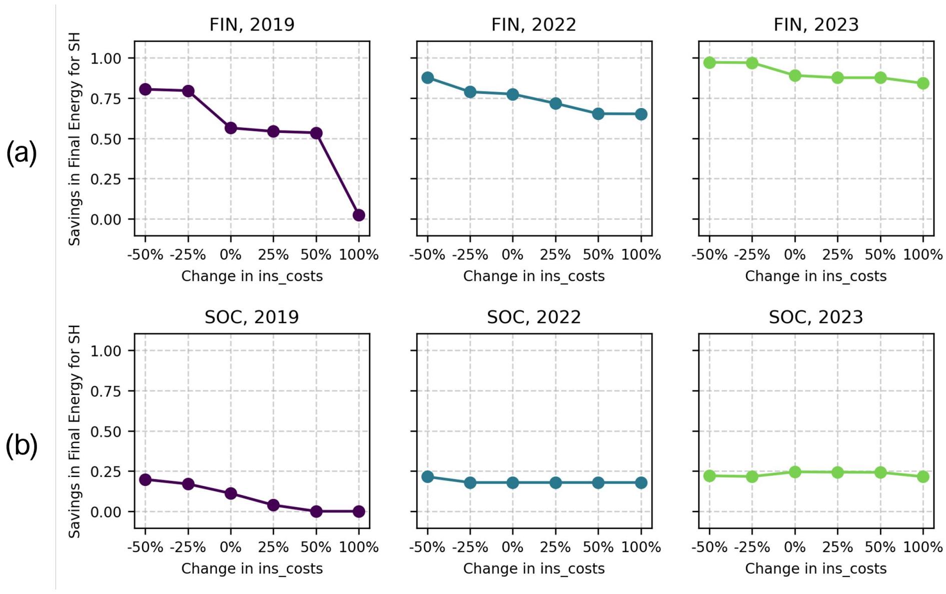


Figure 5.9.: Savings in final energy demand for space heating - sensitivity to insulation costs

The SOC model is highly sensitive to parameters associated with the TPB: agent attitude, intention threshold, and PBC. Figure 5.10 presents the results for savings in final energy demand for space heating in response to variations in these parameters. As shown in Figure 5.10 (a), more positive attitudes toward retrofitting significantly increase savings in final energy demand for space heating, as more agents become inclined to adopt heat pumps and insulation.

Figure 5.10 (b) reveals that lower the intention threshold leads to higher adoption rates of heat pumps and insulation, resulting in increased savings in final energy demand for space heating. This is because lowering the threshold allows more agents to surpass the decision-making threshold required to initiate intention to retrofit. Conversely, raising the threshold restricts many agents from adopting energy-efficient measures, thereby reducing overall savings.

Figure 5.10 (c) highlights that increasing agents' PBC—-i.e., their belief in their ability to undertake retrofits—-boosts the adoption of energy-efficient technologies and leads to higher energy demand savings. This suggests

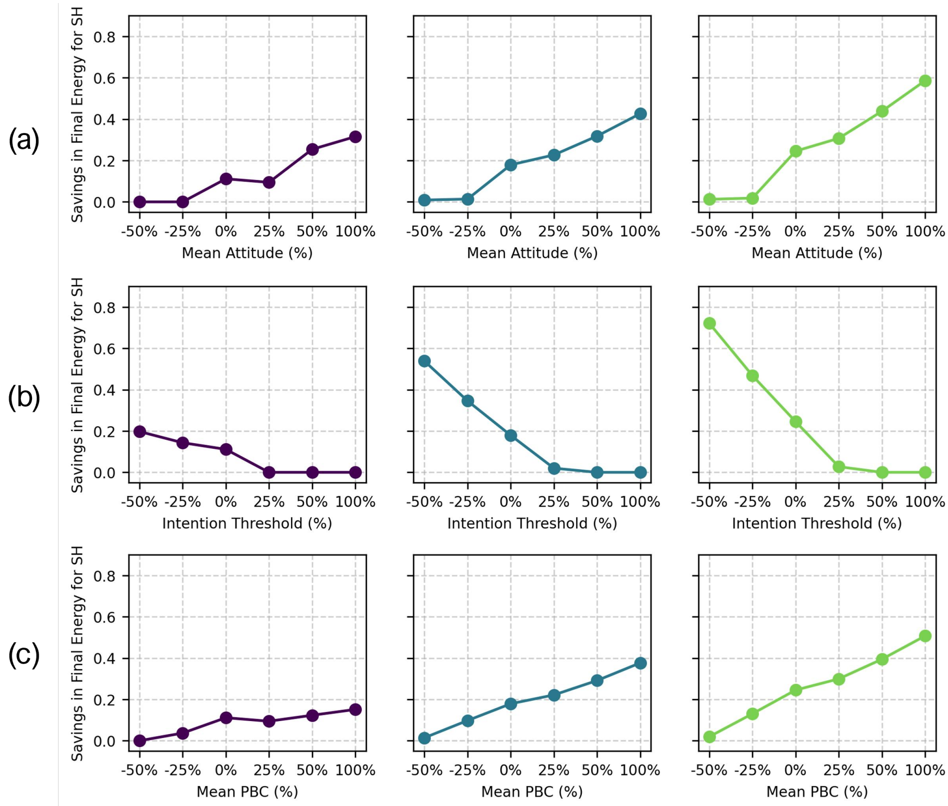


Figure 5.10.: Savings in final energy demand for space heating - sensitivity to (a) Mean Attitude, (b) Intention Threshold and (c) Mean PBC in the population

that enhancing agents' sense of control and reducing perceived barriers to retrofitting could be critical in driving widespread adoption of sustainable technologies in the *SOC* framework.

Changes in mean attitude, mean PBC, and intention threshold all similarly affect *SOC* results. Among these, the intention threshold shows the most pronounced effect on adoption rates and energy savings, as lowering it enables more agents to surpass the decision-making threshold for retrofitting. This is followed by agent attitude, where more positive attitudes lead to higher adoption rates. Changes in PBC have a relatively smaller but still significant impact, as they enhance agents' perceived ability to undertake retrofits. Balancing these three variables is crucial (see Section 5.2.3), although the optimal combination ultimately depends on the expected heat pump adoption rate.

5.4. Discussion

5.4.1. Findings and insights

Rational homeowners evaluating the NPV of retrofit options often transition to heat pumps with or without insulation, especially in older, inefficient houses. This aligns with studies on the cost-effectiveness of energy-efficient retrofits (Ürge-Vorsatz et al., 2009; Wilson et al., 2015). However, the simulation results reveal distinct differences between the techno-economic and socio-psychological decision-making models, offering novel insights into retrofit adoption dynamics. The techno-economic model, focused on financial metrics such as NPV, projected higher adoption rates for heat pumps, particularly in scenarios with strong financial incentives and favourable energy prices. These findings reinforce the critical role that financial incentives play in driving retrofits, while also highlighting the limitations of relying solely on financial considerations without addressing behavioural and social factors.

The socio-psychological framework, which factors in homeowner attitudes, PBC, and social norms, presents a different picture. The model showed lower adoption rates for technologies like heat pumps and a stronger preference for traditional options such as gas boilers. This outcome is particularly relevant in contexts where financial incentives are weaker, as seen in the Netherlands, where gas boilers have traditionally dominated but adoption patterns began shifting following the energy crisis. The model calibration reflects these dynamics, capturing the strong preference for traditional heating systems while showing that heat pumps are preferred by a subset of agents with a strong intention to retrofit. The *SOC* framework showed a high sensitivity to parameters associated with the TPB. Specifically, intention thresholds play the most critical role in influencing adoption, followed by attitudes and PBC. Lowering intention thresholds—such as by simplifying processes or reducing upfront costs—enables more agents to surpass the decision-making threshold, driving higher adoption rates. Meanwhile, increasing attitudes and PBC improves energy savings but to a lesser extent. These findings highlight that while financial barriers are important, attitudinal and behavioural factors are equally crucial. Policymakers must consider social dynamics and personal attitudes alongside financial incentives to effectively encourage the adoption of sustainable technologies.

This comparison brings to light the critical role that the choice of decision framework plays in shaping model outcomes. Based on the socio-psychological model, financial incentives had a limited impact compared to factors like attitudes, perceived control, and subjective norms. These insights suggest that the real-world scenario likely lies between these two extremes. Financial incentives are important, but addressing social and psychological barriers is equally crucial to encouraging widespread adoption of energy-efficient technologies.

The policy scenarios tested in our model offer further innovative insights into intervention strategies. While subsidies, as expected, significantly boost heat pump and insulation adoption (Rosenow et al., 2017; Stadelmann and Castro, 2014) in the techno-economic decision-making framework, our results show that these same subsidies have limited impact based on the socio-psychological model. Here, a ban on gas boilers was more successful in driving sustainable heat transitions. This finding underscores that in contexts where social and psychological factors are barriers, stronger regulatory measures may be required. However, this ban could result in pre-emptive behaviour, with homeowners replacing boilers before the 2026 deadline to avoid future restrictions. This potential unintended consequence, often neglected in previous studies, suggests that timing and communication of regulatory measures must be carefully considered to avoid adverse outcomes.

Furthermore, our results indicate that future gas price expectations and the affordability of heat pumps (which our model does not fully account for) are important factors that could influence decision making. While we did not include detailed affordability assessments, existing low-interest loans in the Netherlands, such as those offered by Warmtefonds, could alleviate financial barriers for some homeowners (Nationaal Warmtefonds, n.d.). Future work should integrate these financial support mechanisms into the model for a more comprehensive analysis of their potential impact.

Energy savings and emissions reductions further reveal the novel contributions of our study. In the financial model, the simulations achieved up to 90% savings in final energy demand for space heating, a significant improvement over the 20-25% savings in the socio-psychological model. However, these estimates may be overly optimistic due to the exclusion of rebound effects. The rebound effect, where increased efficiency leads to greater energy use, is well-documented in the literature but is not yet integrated into many energy retrofit models (Gillingham et al., 2016; Greening et al., 2000; Aydin et al., 2017). Future research should incorporate dynamic models that simulate these effects and explore policy measures, such as stricter post-retrofit energy regulations, to mitigate rebound behaviours.

This study makes several key contributions to the existing literature. Firstly, while most studies focus on single-technology adoption, our research uniquely examines the interdependencies of multi-technology retrofit adoption (Du et al., 2024; Meles and Ryan, 2022; Sopha et al., 2013; Friege et al., 2016; Chersoni et al., 2022; Huang et al., 2019; Khansari and Hewitt, 2020). Specifically, the decision to adopt a heat pump and insulation is closely linked. Our findings underscore that the effectiveness of a heat pump, measured by its SCOP, is heavily dependent on adequate insulation. Poor insulation significantly reduces SCOP, leading to inefficient heating and failure to maintain desired indoor temperatures (Ounis et al., 2022). This integrated approach highlights the importance of considering multiple retrofit technologies together, a perspective often overlooked in prior studies.

Secondly, our approach provides a novel distinction between the decision to retrofit and the choice of specific retrofit measures, an area often blurred in the existing literature. While TPB is frequently applied to assess general adoption versus non-adoption decisions, it typically does not address the specific measures homeowners choose (Si et al., 2019; McLaughlin and Stephens, 2015). Our research fills this gap by mapping out the distinct stages and decision factors that influence not only whether to retrofit, but also which specific measures to adopt. This detailed analysis provides valuable insights for designing tailored policies and interventions that address both the overall decision to retrofit and the selection of appropriate measures.

Finally, our research bridges the gap between techno-economic models and socio-psychological factors, an area that remains underexplored in existing studies. By incorporating the TPB, our socio-psychological model captures key social influences and personal attitudes that drive retrofit decisions. Unlike conventional techno-economic models that focus solely on financial metrics, our model demonstrates how motivations, perceived control, and social norms impact the intention to retrofit. For instance, agents with high retrofit intentions are more likely to choose comprehensive retrofit packages, prioritising energy savings, convenience, and profitability, while those with lower intention tend to delay action, replacing heating systems only when they fail.

5.4.2. Limitations and Future work

Despite its valuable contributions, this study has several limitations. The lack of detailed empirical data on neighborhood adoption and social factors, such as attitude and PBC, and the lack of validation for decision-making processes are notable. Ideally, a dedicated neighborhood survey would parameterise attitudes, PBC, weights, and intention thresholds, and identify retrofit adopters. This was beyond our research scope. The absence of detailed empirical data, especially microdata, is a recognised issue (Derkenbaeva et al., 2023). Although input parameters are calibrated based on historical data, the parameter values are not unique, leading to inherent uncertainty in modeling such complex systems.

The decision-making strategies in this ABM are not exhaustive or fully representative of real homeowner processes. While research in this area is growing, there is no definitive answer to how homeowners decide to renovate or select specific measures. Many authors support the idea that this is a multi-stage process involving numerous factors at each stage (Broers et al., 2019; Du et al., 2022). Our model considered some decision stages, like renovation consideration and decision, but omitted the post-implementation stage and feedback mechanisms. The model assumes renovation is considered primarily when heating systems fail, ignoring renovations for aesthetic reasons or degradation (Abreu et al., 2020), which are harder to estimate. Furthermore, varying the discount rate 'r' based on individual financial circumstances could add a more personalised economic impacts on renovation decisions.

The model included 38 specific retrofit packages, while real-world options and insulation types are numerous and vary by region. We limited heating systems to fully electric heat pumps, but future research could explore other solutions like district heating and hybrid heat pumps. Additionally, measures such as airtightness improvements and heat recovery ventilation, which are known to significantly impact energy efficiency by reducing heat losses, were not considered in this study. Including these elements in future research would provide a more comprehensive analysis of retrofit measures and their impact on energy savings.

Exploring staged retrofits, where improvements are phased, could reflect realistic practices and reveal long-term effects on energy savings (Maia et al., 2021).

For the calculation of emissions, a constant emission factor for electricity was assumed, although this factor varies depending on the share of renewable electricity in the grid mix (Nowtricity, 2024). Including a wider array of options and varying emission factors could affect the results and provide a more comprehensive understanding of the potential impacts of different retrofit measures.

Enhancing the model by incorporating other stakeholders is also possible. Intermediaries like energy advisors, contractors, and policymakers can reflect their influence on homeowner decisions through advice and incentives. Including landlords in the model is also crucial, as they face different incentives and constraints compared to homeowners. Understanding their decision making can help identify policies that encourage landlords to invest in energy-saving measures. Testing soft policies, such as awareness campaigns and training programs, could further promote energy-efficient retrofits.

Future research should test the model's effectiveness at different scales, from neighbourhoods to entire cities or countries, to understand its adaptability and necessary adjustments. Examining interactions and peer effects in varying community sizes would provide insights into adoption rates and intervention effectiveness.

Addressing these areas would enhance the model's robustness, offering comprehensive insights into the adoption of energy-efficient retrofits and informing effective policy interventions for sustainable residential buildings.

5.5. Conclusion

In this paper, we have introduced an agent-based model to simulate homeowners' adoption of energy-efficient retrofits, integrating techno-economic and socio-psychological decision-making processes. Our findings reveal significant differences: the techno-economic model predicts higher adoption rates due to favourable NPV, while the socio-psychological model shows decisions are influenced by attitudes, PBC, and social norms, leading to a preference for gas boiler replacements.

Policy implications suggest that financial incentives alone are insufficient for widespread adoption. While subsidies impact the techno-economic model, their influence is limited based on the socio-psychological model, highlighting the need to integrate social and psychological factors into policy design. Effective policies should enhance awareness, simplify grant processes, and address financial barriers through low-interest loans.

Our sensitivity analysis shows that changes in mean attitude, PBC, and intention thresholds significantly affect adoption rates, indicating that interventions improving these parameters could enhance adoption. Future research should explore the model's scalability and the impact of staged retrofits and personalised economic variables on decision making.

In conclusion, combining economic incentives with strategies addressing social and psychological factors is crucial to increasing the adoption of energy-efficient retrofits, contributing to reduced energy consumption and environmental impact in line with climate and energy goals.

6. Discussion and synthesis of results

This dissertation provides new insights into the decision-making processes regarding energy-efficient retrofitting, answering three key research questions. The discussion highlights the significance of these findings, the limitations of the analysis within this work and its impact on the results, as well as the directions for future research.

6.1. Discussion of results with respect to the research questions

Through the investigation of three key research questions, this work has aimed to fill the gaps in our understanding of the factors that drive or hinder the adoption of energy-efficient retrofitting measures. The findings offer valuable insights for research and sustainable energy policies, as well as provide recommendations for increasing the adoption of energy-efficient technologies.

The findings with regards to the *RQ1: What kind of homeowners adopt building retrofitting (in the Netherlands)?* reveal that decisions are strongly influenced by a complex interplay of socio-demographic factors, property characteristics, and previous maintenance activities. Wealthier homeowners in larger, rural, single-family houses with higher energy demands are particularly inclined to implement a broad range of energy-efficient retrofits, including solar panels, heat pumps, insulation, and double-glazed windows. In contrast, older and smaller households, especially those who have lived in their homes for a long time, show less propensity to adopt such measures, likely due to perceived financial and practical constraints. Additionally, homeowners with high levels of neighborhood involvement and those in safer, well-educated communities are more likely to adopt retrofits, indicating the significant role of social influence and community trust in driving energy efficiency decisions.

To effectively address the diverse motivations and barriers to energy-efficient retrofitting (EER) identified in this study, several targeted policies are recommended. For older and smaller households, which often face financial constraints and may hesitate to invest in retrofitting due to concerns about upfront costs and long-term returns, a program (similar to “MaPrimeRénov” in France Agence nationale de l’habitat, 2024) which offers substantial financial aid and comprehensive support throughout the renovation process, including initial energy audits to assess needs, assistance with applying for grants, and guidance on selecting the most effective retrofitting measures would be beneficial. A personalised approach would ensure that homeowners receive expert advice tailored to their specific circumstances, making the process less daunting and more accessible. Implementing such a program in the Netherlands could help older homeowners in smaller, long-owned homes improve their energy efficiency, enhance comfort, and reduce energy bills, all while minimising financial and logistical barriers. Similarly, the Czech Republic’s Fix Up Grandma’s House initiative offers upfront subsidies and low-interest loans to make the renovation of older family homes more affordable. This program not only helps families modernise their homes but also supports energy-saving measures and sustainable living, making it a strong example for countries aiming to address similar challenges (IEA, 2024).

The role of community engagement and social factors is also critical. Homeowners who are more integrated into their communities and reside in safer, more educated areas show a higher propensity for adopting energy-efficient measures like solar panels. This suggests that policies aimed at fostering community-based retrofitting initiatives could be highly effective. For instance, the Dutch government could prioritise empowering a core group of individuals to spearhead these initiatives by offering centralised support and structured resources. By doing so, it would help address leadership gaps and promote the successful establishment of Local Energy Initiatives (Ghorbani et al., 2020). By promoting social cohesion and trust, these policies would not only increase the adoption of energy-efficient measures but also strengthen community resilience and engagement in the energy transition.

In addressing *RQ2: How has ABM been used to model policy interventions that facilitate the decarbonisation (i.e., energy transition) of building-related urban district energy systems?*, the findings indicate that ABM has emerged as a versatile and flexible tool for simulating complex interactions and stakeholder behaviors in urban district energy systems, making it particularly valuable for policy design and evaluation. ABMs allow for the bottom-up representation of individual decision-making, while also capturing emergent system-wide phenomena. This dual capability is essential for exploring "what-if" scenarios and understanding the broader implications of specific policy interventions, such as those aimed at decarbonising urban districts. ABMs' ability to model decentralised and diverse actors—households, firms, and governments—positions them as uniquely suited to navigating the complexity of future smart energy systems. However, the scalability of ABMs to reflect increasingly complex systems, such as those driven by prosumers (energy consumers able to produce energy), remains a key challenge.

The use of ABMs in energy systems has focused on areas such as the adoption of energy-efficient technologies and the formation of thermal energy communities, where social interactions significantly influence outcomes. Despite their potential, several challenges remain, including the need for ABMs to evolve to handle the increasing complexity of decentralised energy systems and multi-level decision-making processes, such as those involved in building retrofits or district heating development. Furthermore, there is a notable gap in the integration of empirical data for parameterisation, calibration, validation, and verification, which is crucial for improving the reliability and robustness of these models. Addressing these challenges will enhance ABMs' effectiveness in guiding policymakers towards successful and socially just energy transition strategies in urban districts.

In terms of decision-making models, most ABMs reviewed apply psychological or theoretical frameworks like the Theory of Planned Behavior or Consumat, which help simulate the behavioral and social drivers behind technology adoption. Some models, however, rely on ad-hoc or "rule of thumb" assumptions. While these ad-hoc approaches are easier to implement, they lack the theoretical rigor of validated models and may be less reliable for projecting outcomes. The flexibility of ABMs also allows them to model social dissemination and peer influence, which are crucial for understanding how community-driven initiatives can enhance the uptake of energy-efficient measures. Unfortunately, there is often a lack of empirical data to adequately parameterise such social interactions, which can limit the real-world applicability of ABMs. Further research into how these social dynamics influence retrofit adoption could enhance the ability of policymakers to create more effective community-based interventions.

In relation to *RQ3: How do techno-economic and socio-psychological decision-making rationales impact energy-efficient retrofitting adoption?*, the analysis underscores how different frameworks—techno-economic and socio-psychological—impact the adoption of energy-efficient retrofitting. The techno-economic model, focused on financial metrics such as NPV, projected higher adoption rates for advanced technologies like heat pumps, particularly in scenarios with strong financial incentives, high energy prices, and easy access to capital. In these contexts, financial incentives play a crucial role in driving retrofits.

However, the socio-psychological model, which factors in homeowner attitudes, PBC, and social norms, presents a different picture. It showed lower adoption rates for technologies like heat pumps and a stronger preference for traditional options such as gas boilers, especially where financial incentives were less prominent and social or cultural preferences favored familiar systems. This outcome is particularly relevant in contexts where financial incentives are weaker, where there is a strong cultural or social preference for traditional heating systems, or where there is a higher level of uncertainty or perceived risk associated with newer technologies. These findings suggest that while financial incentives can be powerful motivators, they may be insufficient to drive widespread adoption without also addressing the psychological and social factors that influence homeowners' decisions.

This comparison brings to light the critical role that the choice of decision framework plays in shaping model outcomes. In the socio-psychological model, financial incentives had a limited impact compared to factors like attitudes, perceived control, and subjective norms. These insights suggest that the real-world scenario likely lies between these two extremes. Financial incentives are important, but addressing social and psychological barriers is equally crucial to encourage widespread adoption of energy-efficient technologies.

The findings suggest that while financial incentives can be effective, particularly within a techno-economic framework, they are most successful when complemented by regulatory policies that mandate minimum energy performance standards and phase out less efficient technologies. Such regulatory measures create a baseline requirement that can drive widespread adoption of energy-efficient technologies, even among homeowners who might be less responsive to financial incentives alone. Additionally, these policies should be paired with initiatives that address social and psychological barriers, such as awareness campaigns and community engagement programs, to ensure a more holistic approach. A combined strategy that integrates financial incentives, regulatory policies, and measures to overcome social and psychological barriers is essential for achieving significant energy savings and carbon reductions.

6.2. Limitations

The research presented in this thesis, while providing significant insights into energy-efficient retrofitting and urban district energy systems, faces several limitations that warrant further exploration.

The limitations of the empirical analysis within this thesis include the lack of key variables, such as awareness of energy efficiency and available subsidies, which are crucial predictors of retrofit decisions. Additionally, the cross-sectional nature of the survey limits our ability to observe changes in attitudes or behaviors over time. Conducting panel surveys in future research would enable a more dynamic understanding of retrofit adoption.

One of the major challenges in leveraging ABMs for policy-making lies in the integration and validation of empirical data. While ABMs are widely recognised for their potential to guide policy through realistic simulations, many models fail to adequately incorporate empirical data for parameterisation, calibration, and validation. This lack of detailed empirical grounding is a critical limitation, as it affects the reliability of the results. The process of calibrating and validating models with real-world data is essential for ensuring that ABMs can produce actionable insights for policymakers. However, obtaining high-quality, granular data on decentralised systems and community-driven energy transitions is difficult. Addressing this gap, alongside efforts to scale up ABMs for more complex, multi-level decision-making systems, will be crucial for unlocking their full potential in driving effective and socially just energy transition policies.

The lack of detailed empirical data on neighborhood adoption behaviors and social factors, such as attitudes and PBC, represents a significant limitation. While values from the literature were used to inform these parameters, the heterogeneity across agents introduces uncertainty into the model's accuracy. Empirical validation remains a challenge, particularly in ensuring that the models accurately reflect real-world dynamics. The reliance on historical data for calibration, without sufficient distinction between calibration and validation processes, further complicates this issue. Collecting granular neighborhood-level data would greatly enhance the model's robustness, though challenges remain in generalising such highly specific data to broader populations.

Another limitation is that the decision-making process is simplified, focusing only on specific stages of decision-making, such as the consideration of renovation, but omitting others, including post-implementation feedback mechanisms. Post-renovation feedback mechanisms, where the experiences of homeowners with completed retrofits influence future decisions and social dissemination, are not considered in this work. This leads to a weaker role and under-representation of dissemination in the neighbourhood. Additionally, this work focuses primarily on economic or technical triggers (e.g., energy price increases or boiler failure). This excludes other critical triggers, such as life events (e.g., moving in, birth of a child) and aesthetic motivations, which also drive renovation decisions. This potentially reduced the occasions for renovating, leading to less adoptions and less energy efficiency overall.

Reflecting on the challenges faced in parameterising the ABM, I initially considered using a discrete choice model (DCM) since it seemed better suited to the available empirical data. However, the Theory of Planned Behavior (TPB) framework appeared more promising based on previous research, as it integrates a broader set of psychological factors relevant to retrofit decisions. Unfortunately, the decision to analyse an existing empirical survey—rather than designing one specifically for the ABM—limited the ability to use the survey results directly to parameterise the model. In hindsight, it is clear that empirical data collection should be tailored to the decision-making framework used in the ABM to ensure coherence and robustness. For instance, a survey designed specifically for a TPB-based ABM would need to capture attitudes, perceived control, and social norms in a way that could be quantitatively integrated into the model.

Going forward, future research should aim to design empirical studies and ABMs in parallel, focusing on specific neighborhoods or communities to capture the contextual variables that drive decisions. This would ensure the ABM is based on empirical data that aligns with its decision framework, improving the accuracy and relevance of the simulations. For example, Ajzen, 2013 provides a guideline for constructing a TPB questionnaire based on their previous work (Fishbein and Ajzen, 2011). Using this guideline to create a custom survey for this ABM would've been the best choice.

The limited scope of stakeholder involvement is another constraint. The model primarily focuses on homeowners, neglecting other key actors, such as landlords, tenants, energy advisors, and policymakers. For instance, rental properties make up a significant portion of the housing stock, yet the unique challenges landlords face, such as the split incentive problem, are not modeled. This could limit the model's relevance in understanding retrofit dynamics in rental properties. Expanding stakeholder representation would provide a more complete picture of the retrofit landscape and improve the model's applicability to policy design.

Technologically, the model's focus on fully electric heat pumps overlooks the growing importance of hybrid heat pumps and district heating systems, which are increasingly being promoted in various national energy strategies. This limitation affects the model's ability to simulate real-world policy scenarios comprehensively. Including a broader range of heating technologies would provide more accurate and diverse insights into policy outcomes, particularly as different regions adopt varying decarbonisation strategies.

Lastly, the model's geographic focus on suburban, single-family homes limits its applicability to more urban settings, particularly those with multi-family apartment buildings. Group decision-making in condominiums or apartment buildings introduces complexities that are not captured in this model, restricting its relevance to densely populated urban areas. For example, Nava-Guerrero et al., 2021 addresses group decision-making with an ABM, highlighting the challenges in coordinating multiple stakeholders in shared living spaces. Additionally, the assumption that retrofit decisions are largely driven by technical triggers, like heating system failures, limits the model's ability to capture the diversity of real-world motivations.

6.3. Future research directions

The empirical analysis in this thesis has several limitations. One key limitation is the absence of important variables, such as homeowners' awareness of energy efficiency, available subsidies, and environmental consequences, which are known to significantly influence retrofit decisions. Without these variables, the model may overlook crucial drivers or barriers that could affect homeowners' likelihood to adopt energy-efficient measures. Additionally, the cross-sectional nature of the survey used in this research provides only a snapshot of homeowners' decision-making at a single point in time. This limits the ability to track changes in attitudes, motivations, or behaviors in response to evolving circumstances, such as new policies, economic shifts, or social influences. To address these limitations, future research could benefit from longitudinal data, such as panel surveys, which would allow for a deeper understanding of how homeowners' attitudes and behaviors evolve over time.

One of the primary limitations of the modelling-based research within the thesis is the lack of granular, neighborhood-level data on homeowner behaviors and social influences. Future research should establish living labs within specific neighborhoods to collect detailed data on homeowner attitudes, behaviors, and retrofit adoption patterns. This data would enhance both the calibration and validation of the agent-based model (ABM), ensuring it reflects real-world dynamics more accurately. Importantly, future studies should tailor empirical data collection to the decision-making framework used in the ABM, ensuring alignment between the data and the model's structure. For example, employing guidelines such as those proposed by Ajzen for the Theory of Planned Behavior (TPB) would provide a structured way to parameterise the ABM effectively. Living labs would also allow for testing policy interventions in real-time, providing immediate feedback and enabling researchers to track changes in attitudes and behaviors over time.

The ABM developed in this thesis simplifies the decision-making process by focusing on economic and technical triggers. Future work should incorporate a wider range of triggers, including life events (e.g., moving, having children) and aesthetic motivations (e.g., home improvement desires). Additionally, introducing post-renovation feedback loops would allow the model to simulate how homeowner satisfaction with completed retrofits influences future decisions and the social dissemination of their experiences to peers. These feedback mechanisms are critical for understanding long-term patterns in retrofit adoption and the social diffusion of energy-efficient behaviors. The choice of decision-making framework plays a big role in this regard, as financial incentives have limited influence in socio-psychological models like TPB, where attitudes, perceived control, and subjective norms dominate. A more comprehensive data collection approach could better inform the model and reflect a balance between financial and behavioral factors.

The model should be expanded to include a broader range of stakeholders, particularly landlords, tenants, energy advisors, and policymakers. Incorporating landlords into the model is essential, especially given their unique incentives and constraints, such as the split incentive problem, where landlords bear the cost of retrofits but tenants benefit from energy savings. Future research could also explore stakeholder-specific decision models that account for landlords' motivations, tenant preferences, and the role of intermediaries like energy advisors. Addressing these perspectives would lead to a more comprehensive understanding of the factors driving retrofitting decisions. The inclusion of these actors would also improve the empirical basis for decision-making, as data on these stakeholders' behaviors could inform model parameterisation and validation.

Currently, the model primarily evaluates the adoption of fully electric heat pumps. Given the growing importance of hybrid heat pumps and district heating systems, future models should incorporate these technologies to reflect the broader range of real-world options available to homeowners. Incorporating time-series data to capture the performance and usage patterns of hybrid systems over time would provide more accurate insights into their adoption potential and impact. This technological diversification would also make the model more applicable to regions with different energy transition strategies. Expanding the technological scope and using real-time data would not only improve accuracy but also ensure that the ABM is validated against more diverse scenarios, strengthening its reliability for policy applications.

The model's current focus on single-family homes limits its applicability in urban settings. Future research should adapt the model for multi-family dwellings and condominiums, where decision-making is often collective. This would involve modeling group decision-making processes within homeowners' associations or property management groups, adding complexity to the decision dynamics. For instance, Nava-Guerrero (2021) addressed group decision-making in an ABM context, highlighting how complex these interactions can be in urban environments. Expanding the model's geographic focus would make it more relevant for urban areas, where a significant portion of retrofit potential lies, especially in high-density housing. Addressing the group dynamics would also necessitate a more context-specific empirical approach, ensuring the data collected is appropriate for modeling collective decision-making processes.

By addressing these limitations, future extensions of the ABM will provide a more robust, comprehensive understanding of energy-efficient retrofitting, offering actionable insights for policymakers and stakeholders across diverse settings. These contributions will push the boundaries of current research, paving the way for more effective and targeted energy efficiency policies and practices.

7. Conclusion and outlook

This thesis aimed to enhance our understanding of energy-efficient retrofitting adoption among homeowners through a multi-dimensional approach, combining both empirical analysis and agent-based modeling (ABM) in parallel to address different but complementary aspects of the retrofit adoption process. These approaches provided distinct insights, with the empirical research focusing on homeowner decision-making factors and ABM exploring how policy interventions might influence these decisions. Through a custom ABM, I demonstrated the differences in outcomes between techno-economic and socio-psychological decision-making models, revealing the importance of addressing both financial incentives and behavioral factors in designing effective retrofit policies.

This research began by investigating the socio-demographic and property factors that influence homeowners' decisions to adopt energy-efficient retrofitting measures. The empirical analysis revealed that wealthier homeowners, particularly those in larger, rural, single-family houses with higher energy demands, are more likely to implement retrofits such as solar panels and heat pumps. In contrast, older and smaller households, especially those who have lived in their homes for a long time, are less inclined to retrofit, highlighting financial and practical barriers. These findings suggest that policies targeting older and financially constrained households could be more effective if they include tailored financial support, comprehensive advisory services, and personalised renovation programs.

Social factors, such as community involvement and neighborhood trust, also emerged as significant drivers of retrofit decisions. Encouraging community-based initiatives that promote collective action and social cohesion could be a key strategy for increasing retrofit adoption. By fostering environments where social influence and shared goals motivate homeowners, neighborhood-wide retrofitting programs and local energy initiatives can become powerful tools. Programs that empower local leaders and create peer-to-peer advisory networks can be particularly effective, as homeowners tend to rely on trusted figures within their communities when making decisions.

In parallel, this research explored how agent-based modeling (ABM) has been applied in energy research to model policy interventions. ABMs' flexibility in integrating psychological frameworks, social influence, and decentralised decision-making makes them well-suited for exploring community-based energy transitions. However, significant challenges remain. Although this study initially aimed to incorporate empirical survey data into the ABM, it became clear that the survey results were unsuitable for direct integration, reflecting a broader issue in the field—obtaining and incorporating empirical data into ABMs is not straightforward. This limitation underscores the need for stronger cooperation between social scientists and engineers to establish workflows and standards for integrating empirical observations into ABM development.

In addition to the empirical challenges, this study attempted to address the complexity of homeowners' retrofit decisions by contextualising them through multi-level decision-making frameworks, which considered a broader range of factors compared to the simpler purchase-based approaches prevalent in prior research. Despite these efforts, much remains to be done. To truly capture the complexity of retrofit decisions, more detailed and contextualised data samples are needed.

The choice of decision-making framework and the factors influencing those decisions play a crucial role in understanding retrofit adoption. In this study, the comparison between the techno-economic and socio-psychological models highlighted this. The socio-psychological framework demonstrated that financial incentives had a limited role compared to core decision variables such as attitude, perceived control, and subjective norms. While the techno-economic model placed financial support at the center of decision-making, the socio-psychological approach emphasised the broader influence of individual perceptions and social pressures. This suggests that the reality is likely somewhere between these two perspectives, where financial incentives are important but cannot work in isolation.

For future ABM applications, it is critical to align the empirical data collection methods with the chosen decision framework. In cases where the socio-psychological approach is adopted, surveys and other data collection methods should focus on capturing attitudes, social norms, and perceptions of control. By tailoring the data collection to the specific neighborhood and the decision-making framework being used, ABMs can better represent the complexity of real-world decision-making and provide more accurate policy insights. This study highlights the need for interdisciplinary cooperation between social scientists and engineers to develop workflows that integrate empirical data more effectively into ABM simulations, ultimately leading to more robust and contextually accurate models.

This research contributes significantly to the growing understanding of energy-efficient retrofitting and its role in achieving sustainability goals. It has underscored the importance of addressing both financial and behavioral factors in policy design. As the empirical findings demonstrate, financial incentives are necessary but not sufficient; psychological and social factors also play a key role in influencing homeowners' decisions. Therefore, future policies must be holistic, combining economic incentives with targeted support programs that address the diverse motivations and barriers faced by different homeowner groups.

Declaration

I acknowledge the use of ChatGPT [https://chat.openai.com/] to paraphase or rewrite some paragraphs in a more succinct way.

I entered the following prompts: "Please rewrite this paragraph in a succinct way"

After checking for correctness, I used the output either directly or with modifications in the dissertation.

List of own publications

7.1. Contributions for the thesis

Akhatova, A., Derkenbaeva, E., van Leeuwen, E., Kranzl, L., Halleck Vega, S., and Hofstede, G.J. (2024).“Who invests in energy retrofits? Mining Dutch homeowners’ data.” *Energy Policy* 189, p. 114132. DOI: 10.1016/j.enpol.2024.114132.

Akhatova, A., Kranzl, L., Schipfer, F.and Heendeniya, C.B. (2022) “Agent-Based Modelling of Urban District Energy System Decarbonisation—A Systematic Literature Review.” *Energies* 15(2), 554. DOI: 10.3390/en15020554

Akhatova, A. and Kranzl, L. (2024). “Agent-based modelling of building retrofit adoption in neighborhoods.” *Under review (Major revision) at Energy and Buildings*

7.2. Other contributions

Bruck, A., Casamassima, L., Akhatova, A. (2022). “Creating Comparability among European Neighbourhoods to Enable the Transition of District Energy Infrastructures towards Positive Energy Districts.” *Energies 2022* 15(13), p. 4720. DOI: 10.3390/EN15134720.

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Appendices

Appendix A.

Supporting materials for Chapter 5

A.1. Input parameters

A short description of the retrofitting packages included in the ABM are demonstrated in Table A1. The values of heating energy need after the renovation and the costs of these packages are provided in the Excel calculation tool, provided as a supplementary material.

Some input parameters used for the simulation are presented in Table A2.

[1] Air exchange by infiltration, $h^{-}1$

Table A1.: Resume of the retrofit packages

Retrofit package (RP)	Insulation	Heating system	Infiltration[1]
Heat pump (HP) only	none	Electric heat pump (EHP) SCOP = 2.5	0.4
HP+deep full ins.	deep	EHP, SCOP = 3.8	0.1
HP+deep walls&floor ins.	deep	EHP, SCOP = 3.4	0.1
HP+deep walls&double-glazing	deep	EHP, SCOP = 3.7	0.2
HP+deep walls&roof ins.	deep	EHP, SCOP = 3.4	0.2
HP+deep floor&double-glazing	deep	EHP, SCOP = 3.6	0.2
HP+deep floor&roof	deep	EHP, SCOP = 3.3	0.2
HP+deep roof&double-glazing	deep	EHP, SCOP = 3.5	0.2
HP+deep walls	deep	EHP, SCOP = 2.9	0.2
HP+deep floor	deep	EHP, SCOP = 2.6	0.2
HP+deep roof	deep	EHP, SCOP = 2.8	0.2
HP+mod. full ins.	moderate	EHP, SCOP = 3.7	0.2
HP+ mod. walls & floor ins.	moderate	EHP, SCOP = 2.7	0.2
HP+mod. walls & double glazing	moderate	EHP, SCOP = 3.0	0.2
HP+mod. walls & roof ins.	moderate	EHP, SCOP = 2.6	0.2
HP+mod. floor & roof ins.	moderate	EHP, SCOP = 3.1	0.2
HP+mod. floor & double glazing	moderate	EHP, SCOP = 3.2	0.2
HP+mod. roof & double glazing	moderate	EHP, SCOP = 3.2	0.2
HP+double glazing	moderate	EHP, SCOP = 2.9	0.2
Gas boiler (GB) only	none	Gas boiler	0.2
GB+deep full ins.	deep	Gas boiler	0.2
GB+deep walls&floor ins.	deep	Gas boiler	0.1
GB+deep walls&double-glazing	deep	Gas boiler	0.2
GB+deep walls&roof ins.	deep	Gas boiler	0.2
GB+deep floor&double-glazing	deep	Gas boiler	0.2
GB+deep floor&roof	deep	Gas boiler	0.2
GB+deep roof&double-glazing	deep	Gas boiler	0.2
GB+deep walls	deep	Gas boiler	0.2
GB+deep floor	deep	Gas boiler	0.2
GB+deep roof	deep	Gas boiler	0.2
GB+mod. full ins.	moderate	Gas boiler	0.2
GB+ mod. walls & floor ins.	moderate	Gas boiler	0.2
GB+mod. walls & double glazing	moderate	Gas boiler	0.2
GB+mod. walls & roof ins.	moderate	Gas boiler	0.2
GB+mod. floor & roof ins.	moderate	Gas boiler	0.2
GB+mod. floor & double glazing	moderate	Gas boiler	0.2
GB+mod. roof & double glazing	moderate	Gas boiler	0.2
GB+double glazing	moderate	Gas boiler	0.2

Table A2.: Parameters

Parameter	Value	Reference
Number of agents	100	
Number of detached + semi-detached houses / terraced houses	0.2	
Value Added Taxes (VAT)	21%	
Gas boiler efficiency	95%	
Heat pump full load hours	1640	(Rijksdienst voor Ondernemend Nederland (RVO), 2022)
Insulation depreciation time	30 years	
Discount rate	5%	
Investment timeframe	20 years	
Consideration time (T_{cons})	3 years	
Weight of the attitude parameter (w_{att})	0.47	Conradie et al., 2023
Weight of the SN parameter (w_{att})	0.19	Conradie et al., 2023
Weight of the PBC parameter (w_{att})	0.34	Conradie et al., 2023
Opinion dynamics rate (μ)		
Number of contacts of each agent i ($N_{contact}$)	3	
Emission factor of natural gas (gaseous)	0.203	(P.J. Zijlema, 2020)
Emission factor of electricity in the Netherlands	0.421	(Nowtricity, 2024)

A.2. Heating system assumptions

Depending on the level of insulation, the heat pump's seasonal coefficient of performance (SCOP) changes (i.e. the better the insulation, the higher the SCOP). The values are estimated based on the work by Günther et al., 2020. We assume that the old central heating radiators are kept, hence there are no additional costs for heat infrastructure acquisition. The nominal power of the heat pump for each house i an retrofit option j, $P^i_{hp,j}$, is calculated by dividing the annual thermal energy need of agent i, $Q_{H,nd,j}$ after retrofit j by the full load hours of operation H_{hp} (see Eq. A.1) provided in Table A2.

$$P^i_{hp,j} = \frac{Q^i_{H,nd,j}}{H_{hp}} \tag{A.1}$$

The specific cost of the heat pump, $c_{hp,j}$, is based on the local market prices for the heat pumps The Sunshine Company, n.d. and is derived as a function of its nominal (thermal) power $P_{nom,j}$ (see Eq. A.2). The overall costs are provided in the supplementary Excel file. All costs include the Dutch Value Added Tax (VAT) rate of 21% and are real prices, i.e. after it has been adjusted for inflation.

$$c_{hp,j} = 7000 + 567 * (P_{nom,j} - 4) \tag{A.2}$$

A.3. Heating system lifetime calculation

The lifetime of an old gas boiler (i.e. condensing, combi gas boiler is a default heating system for all agents at the start) is assumed to be different for each agent and is drawn from the Weibull distribution in Eq. A.3.

$$f(t_{boiler}; k, \lambda) = \begin{cases} \frac{k}{\lambda}\left(\frac{t_{boiler}}{\lambda}\right)^{k-1} e^{-(t_{boiler}/\lambda)^k} & t_{boiler} \geq 0 \\ 0 & t_{boiler} < 0 \end{cases} \tag{A.3}$$

where k is the shape parameter, λ is the scale parameter, and t_{boiler} is the random variable representing the boiler lifetime. As we expect the boiler life expectancy to peak around 15 years, $k = 15$ and $\lambda = 15$. With these parameters, the initial boilers' total lifetimes are spread as shown in Figure A.1.

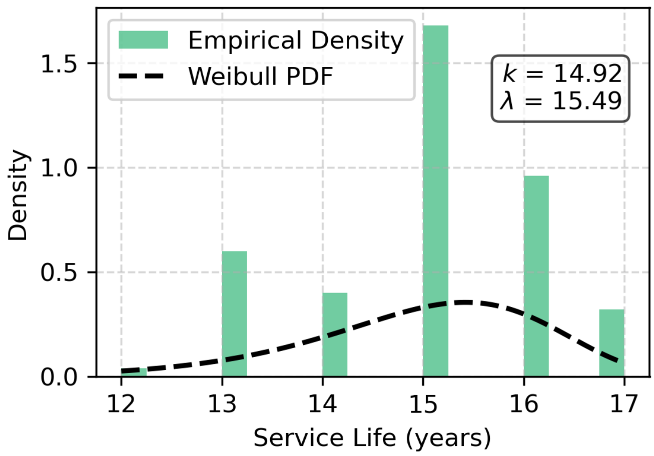

Figure A.1.: A Weibull distribution of condensing gas boilers' service lifetimes

In this model, an agent's current heating system breaks down at some time step. This time is calculated using the assumption that after being constructed, the houses had initially a non-condensing, also known as conventional or low-efficiency, combi gas boiler. This type of system was a standard heating system in the Netherlands between 1960s and 1990s (Weiss et al., 2009). Since the houses we consider were built between 1965 ad 1991, we assume that all of them had non-condensing boilers first and then switched to condensing or high efficiency boilers after the first boiler broke down (i.e. current heating system at the simulation start). To calculate the time of breaking of the current condensing boiler, we need to make following assumptions.

Construction years of agent's houses are set from a random uniform distribution as shown in Eq. A.4. Here a and b are parameters that define the lower and upper bounds of the distribution (i.e. a=1965 and b=1974 for older buildings, a=1975 and b=1991 for newer buildings); t_{house} is any value within these bounds.

$$f(t_{house}; a, b) = \begin{cases} \frac{1}{b-a} & \text{for } a \leq x \leq b, \\ 0 & \text{otherwise.} \end{cases} \tag{A.4}$$

Service life of a non-condensing boiler is taken from the Weibull distribution similar to the condensing boiler (see Eq. A.3), but with different parameters. According to Atlantic Refrigeration and Air Conditioning, Inc., n.d., non-condensing boilers last around 20 years (slightly longer than condensing boilers). Hence, non-condensing boilers' total lifetimes are spread as shown in Figure A.2.

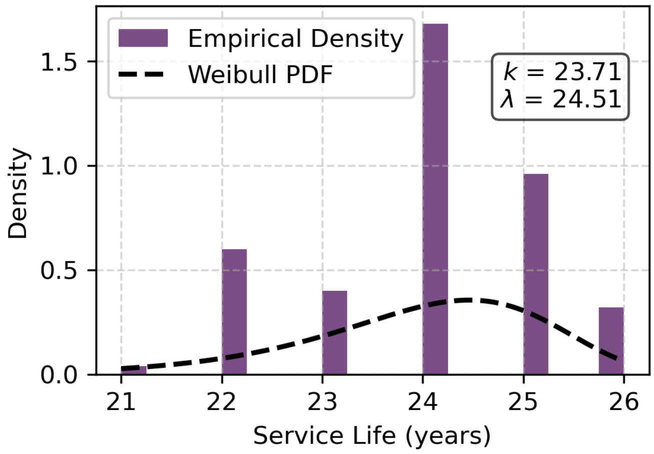

Figure A.2.: A Weibull distribution of non-condensing gas boilers' service lifetimes

Based on these three parameters - construction year of a building, service lives of a non-condensing and of a condensing boilers - we can estimate the breaking time of an agent i's current heating system.

In the simulations, some heating systems break already at the initial time steps. Thus, some agents must replace their boilers second time. The time of second replacement is calculated similarly, just by adding the estimated service life of a previously adopted heating system. Another Weibull distribution is created for heat pumps, with the assumption that air-water heat pumps' average service lives are about 15-20 years (Intuis, n.d.; TermoPlus Heat Pumps, n.d.). This distribution is as depicted in Figure A.3.

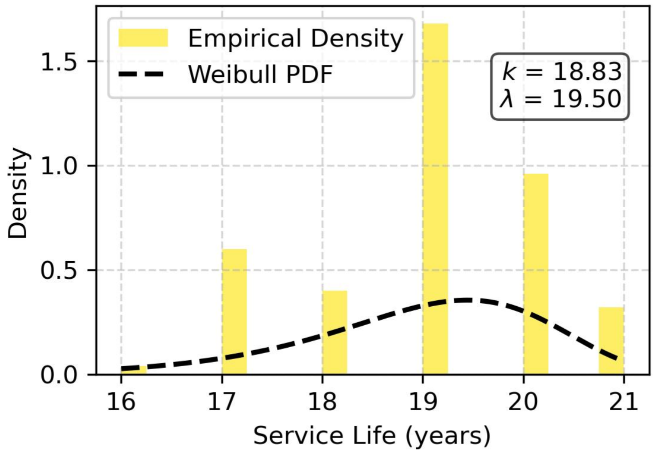

Figure A.3.: A Weibull distribution of air-water heat pumps' service lifetimes

A.4. Price trigger assumption

As Achtnicht and Madlener, 2014 demonstrate, present and expected energy costs are one of the most frequently stated drivers for heating system replacements. However, we assume that it is subject to the current operation year of the boiler. That is, if the current heating system is new enough, e.g. 5 years old, then a very high growth in gas prices would be needed to make an agent replace it upon a price spike. Conversely, if a current heating heating system is older, e.g. more than 10 years, an agent considers replacing it upon even a smaller price growth. This relationship between gas price growth ΔP and threshold age x_{thr} of a current heating system is modelled as in Equation A.5. Upon a price spike, the current age of a boiler is compared against the threshold lifetime x_{thr} and if it is higher than that, an agent considers retrofitting.

The equation is calibrated with the values of $\Delta P = 54\%, x_{tot} = 15, x_{thr} = 11$, which results in $c = 180$.

$$x_{thr} = x_{tot} \cdot \exp \frac{-\Delta P}{c} \tag{A.5}$$

If none of this conditions are true, an agent is not adopting anything in this time step.

A.5. Attitude parameterisation and opinion dynamics

Beta distribution is used to parameterise attitude parameter.

$$f(Att_i(t=0); \alpha, \beta) = \frac{x^{\alpha-1}(1-x)^{\beta-1}}{B(\alpha, \beta)} \tag{A.6}$$

where

- $Att_i(t=0)$ is the random variable,
- $\alpha > 0$ and $\beta > 0$ are the shape parameters of the distribution,
- $B(\alpha, \beta)$ is the Beta function, defined as

  $$B(\alpha, \beta) = \int_0^1 t^{\alpha-1}(1-t)^{\beta-1} dt,$$

  which serves as a normalization constant to ensure that the area under the PDF curve equals 1.

Opinion dynamics sub-model describes how attitude of an agent i changes over time in the simulation. According to Zarei and Maghrebi, 2021, Deffuant's Relative Agreement (RA) model Deffuant et al., 2000 showed superior outcomes, which were very close to the results of the field observations on energy savings derived from eco-feedback program.

In a population of N agents $\epsilon V = 1, 2, ..., n$, each agent has a continuous (real-valued) opinion $x(t) \in (-1, 1)$ and its uncertainty $u \in (0, 2)$. The "Relative Agreement" (RA) model governs how these opinions and uncertainties are modified upon pairwise interaction of agents. Let us consider that each agent has an opinion segment $s_i = [x_i - u_i, x_i + u_i]$ and $s_k = [x_k - u_k, x_i k + u_k]$. The "relative agreement" of agent i with k (not symmetric) is defined as the overlapping part (Eq. A.7) of s_i and s_k minus the non-overlapping part (Eq. A.8) divided by s_i (see Eq. A.9). The overlap h_{ik} is defined as:

$$h_{ik} = min(x_i + u_i, x_k + u_k) - max(x_i - u_i, x_k - u_k) \tag{A.7}$$

The non-overlapping part is:

$$2u_i - h_{ik} \tag{A.8}$$

The relative agreement of agent i with k is expressed as:

$$RA = \frac{h_{ik} - (2u_i - h_{ik})}{2u_i} = \frac{h_{ik}}{u_i} - 1 \tag{A.9}$$

At each time point $t = 0, 1, 2, ..., \inf$, two randomly chosen agents $i, k\epsilon V$ interact and i modifies k's opinion and uncertainty as follows:

$$x_k^{t+1} = \begin{cases} x_k^t + \mu \cdot RA^t \cdot (x_i^t - x_k^t), & \text{if } h_{ik}^t > u_i^t \\ 0, & \text{if otherwise} \end{cases} \tag{A.10}$$

$$u_k^{t+1} = \begin{cases} u_k^t + \mu \cdot RA^t \cdot (x_i^t - x_k^t), & \text{if } h_{ik}^t > u_i^t \\ 0, & \text{if otherwise} \end{cases} \tag{A.11}$$

where μ is a constant parameters that controls the rate of the dynamics.

A.6. Complexity of retrofit packages

Complexity indices are shown in Table A3

Table A3.: Complexity of the retrofit packages

Insulation	**Complexity indices**	
	Heat pump (HP)	**Gas boiler (GB)**
None	0.60	0.20
deep full ins.	0.95	0.70
deep walls & floor ins.	0.90	0.65
deep walls & double glazing	0.85	0.60
deep walls & roof ins.	0.90	0.65
deep floor & double glazing	0.80	0.55
deep floor & roof ins.	0.85	0.60
deep roof & double glazing	0.80	0.55
deep walls ins.	0.80	0.50
deep floor ins.	0.75	0.45
deep roof ins.	0.75	0.45
mod. full ins.	0.95	0.70
mod. walls & floor ins.	0.90	0.65
mod. walls & double glazing	0.85	0.60
mod. walls & roof ins.	0.90	0.65
mod. floor & roof ins.	0.80	0.55
mod. floor & double glazing	0.85	0.60
mod. roof & double glazing	0.80	0.55
double glazing	0.60	0.30

A.7. Calculation of CO_2 emissions

For each agent i, the amount of CO_2 emissions reduction e_{red} from switching from natural gas-based heating to electricity-based heating is calculated by the Equation A.12.

$$e^i_{red} = e^i_{before} - e^i_{after} = Q^i_0 \cdot f_{gas} - Q^i_{use,j}/\eta_j \cdot f_{el} \tag{A.12}$$

where f_{gas} and f_{el} are emission factors of natural gas (gaseous) and electricity in the Netherlands. The values of the emission factors and the sources are included in Table A2.