Positive Energy Districts: A pathway toward urban energy transition?

Erkinai Derkenbaeva

Propositions

1. Energy transition is a necessity for the world and an opportunity for a city. (this thesis)

2. Stakeholders are the heart and the soul of Positive Energy Districts. (this thesis)

3. An agent-based model does not have to represent reality for it to be useful.

4. Microdata regulations hinder rigorous research, even in the Netherlands.

5. Neighborhood cafés can spark collective action.

6. European self-interest can help the rest of the world.

7. Nomad researchers catalyze global conversations.

Propositions belonging to the thesis, entitled

Positive Energy Districts: A pathway toward urban energy transition?

Erkinai Derkenbaeva
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Erkinai Derkenbaeva

Thesis committee

Promotors
Prof. Dr Eveline van Leeuwen
Professor of Urban Economics
Wageningen University & Research

Scientific Director
Amsterdam Institute for Advanced Metropolitan Solutions

Prof. Dr Gert Jan Hofstede
Professor of Artificial Sociality
Wageningen University & Research

Co-promotor
Dr Sol Maria Halleck Vega
Assistant professor, Urban Economics
Wageningen University & Research

Other members
Prof. Dr Arnold Bregt, Wageningen University & Research
Prof. Dr Emely de Vet, Tilburg University
Dr Igor Nikolic, Delft University of Technology
Dr Eleni Stathopoulou, University of Sheffield, UK

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Erkinai Derkenbaeva

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Erkinai Derkenbaeva
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Just because we understand individual parts does not mean that we understand the system composed of those parts.

-Philip W. Anderson, "More is Different" (1972)

To my family

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Chapter 1

General Introduction

1.1. Background

The reliance on fossil fuels, such as coal, oil, and natural gas, has been the backbone of our energy system for over two centuries. While they have provided significant benefits to human societies and economies, they have also come at a cost, leading to environmental degradation, climate change, and energy insecurity. Consequently, there is an urgent need to reconsider the way we produce, distribute, and consume energy. Transitioning to cleaner and renewable energy sources is a key priority in achieving the climate targets set under the 2016 Paris Agreement and United Nations Framework Convention on Climate Change (UNFCCC). The Sustainable Development Goals, particularly (7) Affordable and Clean Energy, (11) Sustainable Cities and Communities, and (13) Climate Action, further emphasize the importance of sustainable energy solutions.

The concept of Positive Energy Districts (PED) has emerged to facilitate the energy transition and contribute to climate neutrality. At the core of the concept, there is a goal to achieve energy efficiency and net-zero energy balance by utilizing low-cost, locally sourced, environmentally friendly energy resources. PEDs are seen as potential pathways toward energy transition and are getting embedded in the energy system largely driven by renewable energy sources aiming to ensure security and flexibility of energy supply. To accelerate its regional transition, the European Union (EU) established the Strategic Energy Technology Plan in 2007 with the goal of developing 100 PEDs by 2025 [1].

The energy transition embarks from the current state of the energy system, which differs across areas, resulting in varying energy transition pathways. The current energy system is at a critical juncture, facing numerous challenges and ongoing transformations. At the heart of this juncture are households being significantly affected and playing a crucial role in these metamorphoses. Traditionally, households have only been consumers of energy, relying on a centralized energy system. However, the transition to a more sustainable and decentralized energy system is shifting households from being just consumers to prosumers (i.e., consumers and producers) of energy, increasing their role in this transformation. Therefore, it will be essential to investigate their adoption behavior and decision-making toward energy-efficient retrofitting (EER) measures and the factors affecting them. In this dissertation, EER includes measures such as insulation of windows, roof, walls, and floor, as well as the adoption of heat pumps and solar panels. As the transition to renewables still requires substantial investments, it can pose the risks of energy poverty and injustice, especially for already vulnerable population groups. Hence, designing policies to support these groups will also be imperative.

This dissertation aims to deepen the knowledge about PEDs development and explore possible pathways toward the energy transition. PED is known as a complex energy system that incorporates multiple interconnected elements, including social and technological sub-systems, which need to evolve in tandem. Therefore, understanding the dynamics within the system and exploring how the interaction among these sub-systems can facilitate the realization of a desired future energy system is imperative. As such, the main focus of this research lies in examining the interplay between households and the essential technologies for achieving the energy transition using the example of the Netherlands, with Amsterdam serving as a primary case study.

Investigating the social and technological interactions within the energy system, as exemplified by households adopting EER measures, can help us gain insights into the dynamics of the current system. This understanding can contribute to exploring potential pathways for a people-centered energy transition, as defined in the PED concept, which is important in addressing energy and climate crises. Based on the findings, this research also aims to outline possible policy interventions that would be effective within a specific Dutch context and useful for other similar areas.

1.2. Research objectives and conceptual framework

The overall objective of this dissertation is to explore pathways toward urban energy transition by 2050 with an intermediate 2030 goal, accounting for area contextual factors and outlining tailored policies based on the findings. To address the objective, this dissertation employs backcasting, an approach that starts with defining a desirable future and then works backward to the present to identify possible steps to achieve it. Figure 1. 1 depicts the conceptual framework of this dissertation with the desirable future set to achieve PEDs by 2050. Each phase in this conceptual framework (A, B, C, D) denotes a study that contributes to achieving the PEDs goal with smaller intermediary steps (i.e., spatial microsimulation, sensitivity analysis, expert validation, and policy design) constituting the research phases. The objectives of each study and the knowledge gaps they aim to address are discussed below.

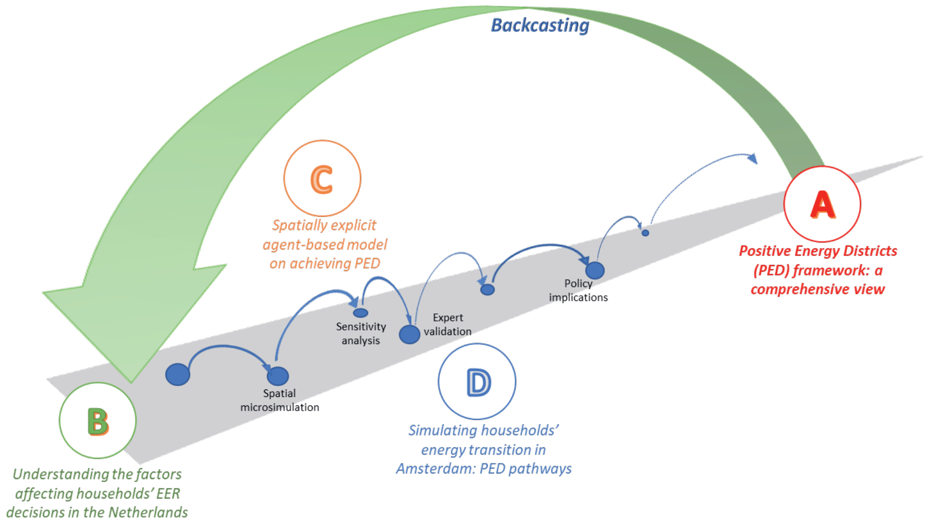

Figure 1. 1. Conceptual framework of this dissertation

PED-related literature has been developing for over a decade, receiving increasing attention due to the severity of energy and environmental crises. However, despite many existing concepts, substantial knowledge gaps and limitations exist. The definitions and assessment metrics across the existing PED-related concepts lack consistency which often causes misinterpretations. The concepts also fail to consider contextual factors that are inherent in real-life PEDs. **Phase A** aims to uncover the notion of PED and develop a more comprehensive view by synthesizing PED-related concepts, reviewing real-life PEDs, and introducing new lenses for a wider focus, such as the system's complexity and resilience. This phase also sets the vision for the future energy system.

As one of the central functions of PEDs, energy efficiency is the first and foremost goal to combat climate change and energy crises. The need for energy efficiency in the Netherlands is particularly urgent as the country still heavily depends on gas imports [2], and its residential buildings are inadequately insulated [3]. Despite the presence of several policies aimed at promoting energy efficiency in residential constructions, there is still significant potential for improvement. **Phase B** aims to determine factors associated with households' investment decisions focusing on four EER measures, including window double-glazing, roof, walls, and floor insulation, solar panels, and installation of heat pumps, and to outline possible policy improvements.

Furthermore, as contextual factors are fundamental for PEDs, it is necessary to zoom into a specific area with its challenges and opportunities. Amsterdam is an interesting example, with its target to drastically reduce carbon emissions by 2030 [4] and the potential to become a leader in the energy transition and a beacon for similar large cities. **Phases C and D** aim to explore how households make EER adoption decisions in Amsterdam and how these decisions differ across the city districts. Additionally, these phases aim to examine to what extent households in Amsterdam can contribute to the city's CO_2 emissions reduction target by achieving PEDs via energy consumption reduction, energy efficiency, and renewable energy generation.

1.3. Theoretical and conceptual approach

The PED concept forms the basis of this research by establishing the goal for a desirable future energy system and serving, as a potential pathway toward achieving it. This concept is relatively new in the context of urban planning and sustainable energy initiatives. The origin and its first use vary depending on different sources and interpretations as there are multiple concepts similar to PED [5]. At the core of the PED and similar concepts is the goal that an urban area is able to meet its energy demands from locally available, financially feasible, and environmentally friendly renewable resources. As there is still no commonly agreed definition of PED, developing a better understanding of the concept and implementing further advancement is necessary. In this dissertation, we enhance its comprehensiveness by integrating it with Complex Adaptive Systems (CAS) and Doughnut Economics, aligning with their core ideas and principles.

CAS offers the notion of a system that comprises multiple individual components that interact. The behavior of such a system cannot be solely defined by the behavior of its individual components but rather by the behavior of the ensemble of these components. Their behaviors generate complexity by creating non-linear dynamics due to interactions at the micro level, which in its turn, cause the emergence of the macro nature of the system [6], which is evidently path-dependent. Furthermore, such complex systems are adaptive as their components dynamically change in response to the changes in the environment at the macro level. As such, the energy system can also be seen as a complex adaptive system comprising multiple sub-systems, including social and technological systems, and being adaptive to the changes in these systems and the environment.

Doughnut Economics embodies two main goals: environmental sustainability and social well-being, which is also central to the PED concept. This framework highlights the boundaries for a social foundation and an environmental ceiling. While meeting the social foundation ensures the safety and well-being of all individuals, avoiding overshooting the environmental ceiling guarantees ecological sustainability [7]. In this study, the "doughnut" represents the desired energy system with the two boundaries potentially achievable via the application of the PED concept. Another key idea from Doughnut Economics that can be extrapolated to the PED concept is the concept of distributive and regenerative dynamics. While distributive dynamics involve sharing the value created with others to ensure equity among all users, regenerative dynamics promote the circularity of resources to limit carbon emissions [7]. The concept of the system's resilience from Doughnut Economics also contributes to the PED concept and the energy transition in general.

Finally, human behavior is driven by a complex interplay of various factors. While economic considerations are undoubtedly crucial for households to meet their basic needs and ensure their well-being, these take place within a context that is primarily relational. That is, while economics determine what is feasible, relations and culture determine what is desirable. Social relational drives refer to the intrinsic human need for social connections, relationships, and a sense of belonging. These drives influence the way households interact with each other, their neighbors, and their broader communities.

To study households' adoption behavior and explore their interaction with society and technologies, this dissertation uses the Consumat meta-model. The Consumat meta-model offers a theoretical framework that comprises macro-level factors shared by all individuals and micro-level factors that differ between individuals affecting their behaviors [8]. In the context of purchase or investment decisions, this framework is well-suited for simulation models that can capture dynamic behavioral processes resulting from the interaction between agents. Using this meta-model for developing the simulation model to explore households' behavior will help capture these dynamic processes and their contribution to the energy transition.

1.4. Methodological approach

A methodological approach in this dissertation can be understood following the lines of thinking of Coleman's boat (Figure 1. 2). At the core of Coleman's boat is the concept of social interconnectedness at the level of society as a whole ("macro-level"), and its impact on individuals' behaviors ("micro-level") and, as a consequence of these behaviors, macro-level system outcomes [9]. It illustrates both how macro-level phenomena influence micro-level ones and how micro components (e.g., behaviors, factors, decision-making) generate macro outcomes.

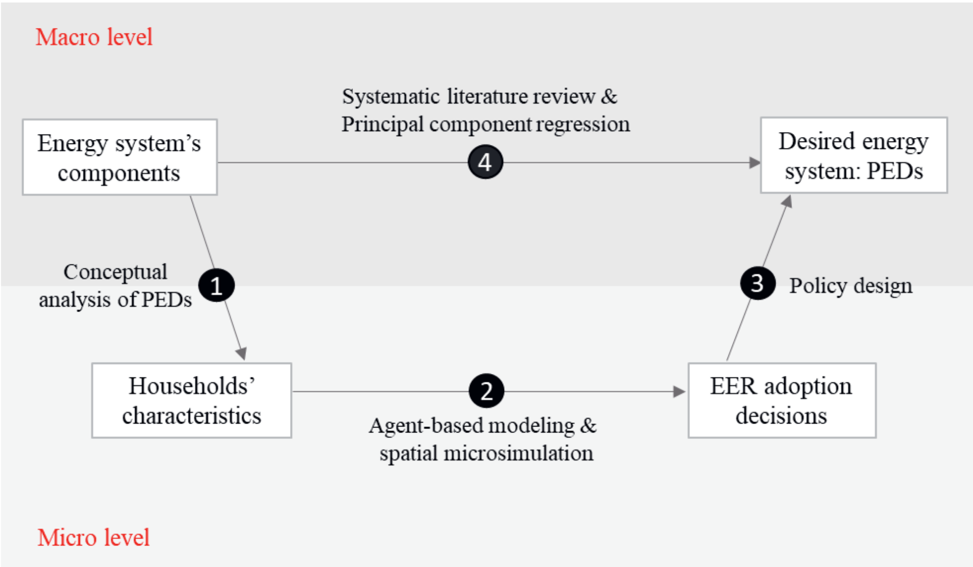

Figure 1. 2. Methodological approach of this study based on Coleman's boat

The main methods used in this dissertation include conceptual analysis, systematic literature review, principal component regression, and agent-based modeling. The results of the conceptual analysis and the literature review served as a reminder of the suitability of Coleman's boat for explaining the methodological approach of this dissertation. This diagram features two levels that are inherent to complex systems.

In this research, the macro level is represented by the energy system that denotes different states at different times – current and future, while the micro level is characterized by households in Amsterdam. At the macro level, the top left corner of the boat represents components of the (current) energy system, such as e.g., technological infrastructure, financial incentives, and regulatory affairs that might explain social phenomena. The top right corner denotes the social phenomenon of this study, which is the transformation of the energy system into PEDs given a certain context. At the micro level, the bottom left corner of the boat refers to the individual properties of agents, also depicted in this study as households' individual characteristics. The bottom right corner represents the behavior and decision processes of individuals caused by their characteristics and their appraisal of their situation. Overall, the four corners of Coleman's boat represent either the articles' input or output.

All arrows of this diagram demonstrate research approaches that have been used in this study and are described below in a consecutive research order. Arrow 1 denotes the conceptual analysis of the PED concept that helps uncover contextual factors that are important for developing PEDs. The next step, arrow 4, represents two activities. First, a systematic literature review in order to identify factors affecting the EER adoption decisions of households. Then, principal component regression analysis is conducted to determine the factors that affect the EER adoption decisions of households in the Netherlands, as these factors might vary across different places. It is a correlational approach that involves analyzing micro-level data at the macro level. Arrow 2 is an agent-based simulation of households' EER adoption decision-making in Amsterdam. This step explores the individual energy-related behavior of agents, their interconnection, and their contribution to a common goal – energy transition. Finally, arrow 3 represents the design of potential policy interventions found to be important for accelerating the development of PEDs in Amsterdam and other similar areas. These policy interventions are designed based on the outcomes of arrows 4 and 2.

The core technique in this study is agent-based modeling (ABM) represented by arrow 2. The ABM is a computational modeling approach to simulate complex systems by representing individual agents and their interactions within an environment. It is a micro-level modeling technique that offers a bottom-up approach to explain macro-level outcomes through causal relationships. The predominant advantage of ABM is its ability to capture the heterogeneity and adaptability of agents and their non-linear interactions that are often present in complex systems [10]. The collective behavior of agents can lead to emergent patterns of system dynamics with top-down and bottom-up causations. Agents dynamically adapting to system-level changes constitutes top-down causation, whereas system-level changes arising as emergent outcomes of agents' collective behavior are referred to as bottom-up causation [10]. Therefore, the ABM is a well-suited and valuable technique for examining households' energy-related decision-making.

The empirical chapters of this dissertation mainly rely on the Dutch Housing Survey *WoonOnderzoek Nederland* (WoON) 2021 [11]. The WoON is a nationwide survey that captures socio-demographic and dwelling information, as well as current and desired living situations and energy-related data. The survey is conducted every three years and uses a stratified sample taken from all Dutch residents 18 years old and older registered with their local municipality.

1.5. Dissertation outline

This dissertation comprises six chapters, including this chapter as General Introduction. The core Chapters 2 to 5 contribute to a specific aspect of the overall research objective (Table 1. 1). Because these chapters are written as independent research articles, they might slightly overlap in discussing their background and motivation.

Chapter 2 offers a comprehensive view on PEDs representing the energy system holistically via the lenses of complexity and resilience. This study unravels how the comprehensive view was developed and reveals the differences between conceptual and real-life PEDs. It also uncovers the main elements of PEDs and contextual factors that play a role in building them.

Chapter 3 provides an understanding of the factors that affect the EER adoption decisions of homeowners in the Netherlands. In light of the contradictory findings in the literature, this study further investigates the interaction between the factors and deriving components to uncover their relationship with EER adoption. The output demonstrates the importance of the area context in EER adoption.

Chapter 4 offers a detailed description of an agent-based model that has been developed to explore how households make EER adoption decisions in Amsterdam. This study uncovers the conceptual and methodological constructs of the model. It also describes sensitivity analysis, validation results, and how to use and adapt the model, making it replicable and accessible to other researchers. As this chapter is more technical, it can be visited after reading Chapter 5.

Chapter 5 presents the key outputs of the agent-based model on homeowners' EER adoption decisions based on the baseline and alternative scenarios across selected city districts. This chapter discusses the implications of the findings and offers a comprehensive understanding of various possible pathways that Amsterdam can take toward achieving a successful energy transition via PEDs.

Chapter 6 synthesizes the four studies by highlighting their main findings, reflecting on the conceptual and methodological implications, and outlining avenues for future research. This chapter also offers possible policy interventions for effective PEDs development and addresses the contributions of this dissertation to science and society.

Table 1. 1. Overview of the main chapters of this dissertation

Chapter	Type	Aim	Method	Backcasting phase
Chapter 2	Conceptual	To uncover the notion of PEDs and develop a more comprehensive view on the PED concept	Synoptic literature review & case study analysis	A
Chapter 3	Empirical	To determine factors associated with homeowners' EER adoption decisions in the Netherlands	Systematic literature review & principal component regression	B
Chapter 4	Design	To describe the ENERGY Pro model in detail using the ODD+D protocol	Agent-based modeling & spatial microsimulation	C
Chapter 5	Empirical	To explore households' EER adoption decision-making across the districts in Amsterdam and their contribution to the city's CO_2 emissions reduction goal	Agent-based modeling & spatial microsimulation	D

2

Chapter 2

Positive Energy Districts: Mainstreaming energy transition in urban areas

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Abstract

The concept of Positive Energy Districts (PED) has emerged to facilitate the energy transition and contribute to climate neutrality through energy efficiency and net-zero energy balance. There are several similar concepts with a common goal that a building, neighborhood, or district can meet its energy demands from low-cost, locally available, environmentally friendly renewable sources. However, there is a lack of comprehensiveness and consistency among these existing concepts that could lead to misinterpretations. Therefore, the main aim of this study is to develop a comprehensive view on the PED concept with a focus on urban residential areas in Europe, with insights also being useful for other areas. The analysis is based on a literature review of PED and similar concepts, as well as a review of PEDs practical examples. The literature review compares PEDs based on geographical scale, identifying defining elements and metrics that provide insights on how to define and operationalize PEDs. The study reveals that real-life PEDs tend to go beyond the frames set by the definitions because the concept fails to consider the contextual factors that are inherent in them. To develop a comprehensive concept of PED, a Complex Adaptive System approach is taken, also incorporating the Doughnut view, which represents the system holistically. This view is also important in designing a resilient system, as energy systems are often exposed to disruptions. Additionally, the study discusses the PED concept's limitations and key issues, such as electric mobility, that merit more attention.

2.1. Introduction

Energy transition has become a priority to achieve the Sustainable Development Goals, particularly, (7) Affordable and Clean Energy, (11) Sustainable Cities and Communities, and (13) Climate Action. This commitment has been reflected in various programs such as *Energiewende* [12], the 2015 United Nations Sustainable Development Goals, and in the global climate action agenda under the 2016 Paris Agreement and United Nations Framework Convention on Climate Change (UNFCCC) [13]. A challenge connected with energy transition is energy poverty: inaccessibility and prohibitive cost of renewable energy services [14], [15]. Evidently, climate change and energy poverty are urgent concerns and require transitioning to more sustainable yet reliable energy systems.

The energy system transformation incorporates socio-economic, technological, environmental, political and institutional challenges that need to be tackled simultaneously. As part of a holistic urban strategy, the innovative concept of Positive Energy Districts (PED) emerged to facilitate the transformation. PEDs are embedded in urban and regional energy systems dominantly driven by renewable energy aiming to provide security and flexibility of energy supply [16]. As such, PEDs have become an integral part of sustainable urbanization strategies. The European Union (EU) has introduced the Strategic Energy Technology Plan with a target to establish 100 PEDs by 2025 [1] in order to contribute to climate neutrality through energy efficiency and net-zero energy balance.

PEDs arose from earlier concepts with comparable meanings [5]. Extensively discussed concepts and terms include *(Net) Zero Energy Buildings* [5], [17], [18], [19], [20], *Nearly Zero Energy Buildings* [21], *Energy Positive Neighborhoods* [22], [23], [24], [25], *Positive Energy Blocks* [26], [27], *Energy Neutral Districts* [28], and *Positive Energy Districts* [1], [16], [29]. A key common thread among these concepts is the goal that a building, neighborhood, or district is able to meet its energy demands from low-cost, locally available, environmentally friendly renewable sources. However, there is still no commonly agreed definition of PEDs. The definitions remain generic, and their variety allows for different interpretations. Since PEDs are the most recently used concept by the EU to indicate local-level energy transition, it is meaningful to develop a consistent conceptual framework of PED that represents the common essence of existing concepts and that is more inclusive by bringing in key elements that are currently largely lacking.

This study significantly contributes to the literature by developing a comprehensive view on the PED concept and integrating the Complex Adaptive Systems (CAS) and Doughnut Economics views into PED. These two frameworks enrich the PED concept by comprising the complexity and resilience of PEDs to boost the local energy transition. The aims are to synthesize concepts related to PED, review practical examples of PEDs, and develop a comprehensive view on PEDs. Synthesizing the concepts will grant an overview of existing PED and similar definitions, allowing to identify key knowledge gaps. Then, zooming in on practical examples of already implemented PEDs in Europe will enable a better understanding of how the conceptual and practical advancements differ, as well as which elements prevail in practice that are missing in the concepts. Finally, based on these overviews, a more comprehensive view on PEDs is developed incorporating insights from CAS and Doughnut Economics views [7], [30]. PEDs as CAS are seen through the lens of Doughnut Economics that recognizes the systemic nature of the economy with an emphasis on climate neutrality and energy poverty.

The remainder of the article is organized as follows. Section 2.2 introduces the approach taken for the development of the comprehensive view on the PED concept. Section 2.3 presents an overview of the existing concepts related to PEDs and discusses assessment metrics for analyzing energy performance. Section 2.4 illustrates practical examples of PEDs implemented in Europe at different scales. Based on both the conceptual and practical advancements of PEDs, Section 2.5 develops a comprehensive view on PEDs, and discusses limitations and key issues that merit more attention. Section 2.6 finalizes this study with concluding remarks.

2.2. Materials and Methods

The focus of this study is on urban residential areas due to their importance in the energy transition process. The analysis is based on a comprehensive literature review of PED and similar concepts, and a critical review of PEDs practical examples. The literature review of the conceptual foundation of PED is carried out based on geographical scale, identifying defining elements and assessment metrics. This fills a gap in the literature, as previous studies have not compared the elements and metrics of PED-related concepts based on geographical scale.

The review of the practical examples provides a representation of possible scales for implementation and variations of different solutions for real-life PEDs. These examples are selected from several PEDs that have already been implemented in Europe. In this study, a list of selected PEDs and information on them is based on the *Booklet of PEDs* [31] and *Value Generation by PEDs: Best Practices Case Study Book* [32]. Additional information is collected from the official websites of the selected PED projects [33], [34], [35], [36], [37], [38]. The examples' selection was guided by a set of criteria [32]: (1) needs to contribute to energy generation, distribution, and management; (2) has to be implemented and operational; (3) aims to address social aspects; (4) has a focus on Europe. These criteria are derived from the reference framework for PEDs based on the EU Strategic Energy Technology Plan [16] that suggests the definition of PEDs.

The PEDs examples satisfy these criteria. However, Derkenbaeva et al. (2020) use the term "PED-like" areas highlighting that despite satisfying the abovementioned criteria, some of the examples are not fully PEDs or are projects that contributed to PEDs implementation. Both the *Booklet of PEDs* [31] and *Value Generation by PEDs: Best Practices Case Study Book* [32] present a large number of examples including PED areas and other related projects.

Because the scope of this study is residential areas, only PEDs implemented in residential areas have been selected from the two mentioned lists, which are in total 11 examples. These 11 PEDs examples are discussed further.

Together, the review of PED-related concepts and practical examples serve to provide a more comprehensive view on PEDs (Figure 2. 1). This is in turn useful for identifying how PEDs differ in their concept and practice, what lenses PEDs should be seen through, discovering knowledge gaps, and formulating an ideal vision for conceptualizing and implementing PEDs.

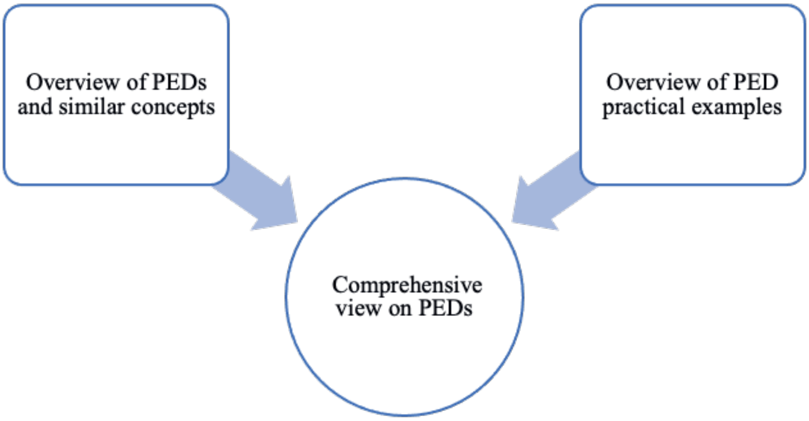

Figure 2. 1. Steps in developing a comprehensive view on PEDs

2.3. The state of the art on PEDs

This section presents an overview of the differences in defining elements and assessment metrics. PED-related literature has been developing for more than a decade, receiving increasing attention due to the severity of energy and environmental crises. At the core of the PED concept is the ambition to overcome these crises. PEDs are viewed as a pivotal means of contributing to a transition away from fossil fuel dependence towards the use of more renewable energy and achieving climate neutrality.

2.3.1. Defining PEDs

While earlier studies have mostly focused on individual buildings, recent studies extend the boundaries to neighborhood and district scales. The existing concepts include the following defining elements that are consistent across the *(Net/Nearly) Zero Energy Buildings* (ZEB)/ *Energy Positive Neighborhoods* (EPN)/ *Positive Energy Blocks* (PEB)/ *Energy Neutral Districts* (END)/ *Positive Energy Districts* (PED): (1) a geographical boundary; (2) a state of interaction with an energy grid; (3) an energy supply method; and (4) a balancing period (see Table 2. 1). The overview is based on the central distinct element – geographical boundary, while the other elements vary within the geographical boundary. It is important to define a clear geographical boundary because specified areas (a building, a neighborhood, or a district) are treated as a single unit with demand, local supply, and storage [24] addressing the scale of an energy-efficient area.

Building scale

Definitions of the ZEB/EPN/PEB/END/PED may vary depending on local contexts and goals of stakeholders – policymakers, investors, energy users. Therefore, Torcellini et al. (2006) propose four different definitions of *Zero Energy Building* (ZEB): (1) *Net Zero Site Energy Building* that produces as much energy as it uses annually when accounted for at the site, (2) *Net Zero Source Energy Building* that produces at least as much energy as it uses annually when accounted for at the source[1], (3) *Net Zero Energy Emissions Building* that produces at least as much emissions-free renewable energy as it uses from emissions-producing energy sources, and (4) *Net Zero Energy Cost Building* that receives as much financial credit for exported energy as it is charged on the utility bills. Among these four definitions, the site ZEB is the most consistent definition because it can be verified through on-site measurements and has the fewest external fluctuations that influence the ZEB goal. In contrast, the source, emissions, and cost ZEBs are not consistent and cannot be measured directly because site-to-source factors need to be determined and there are unpredictable fluctuations in energy costs [17].

Sartori et al. (2012) refer to a ZEB as "an energy-efficient building able to generate electricity, or other energy carriers, from renewable sources in order to compensate for its energy demand." However, the authors point out that this definition is more general and includes autonomous buildings that do not interact with the energy grids (including electrical grids and heat networks), while the term Net ZEB indicates the connection to the grid (smart grid), which enables two-way interaction. Similarly, Marszal et al. (2011) also discuss the differences between a ZEB and Net ZEB through the lenses of the terms "off-grid[2]" and "on-grid[3]" ZEB. The "on-grid" ZEB or a Net ZEB is favored due to the vitality of two-way interaction in order to avoid the issue of large storage capacity, backup generators, energy losses while storing and overproducing the energy [5]. In line with this, the authors highlight a number of requirements that should be considered before Net ZEBs are constructed to comply with the term "on-grid" ZEB. The prerequisites include energy efficiency, indoor climate, and building-grid interaction. Kolokotsa et al. (2011) also highlight that the presence of the "two-way" is essential, with the aim of resulting in a net-positive or zero export of power from the building to the electrical grid. "Two-way" flow in combination with minimization of the energy consumption and energy generation based on renewable energy

[1] Refers to the primary energy used to generate and deliver the energy to the site [17].

[2] ZEB is not connected to any utility grid and hence needs to use some electricity storage system for periods with peak loads and also known as 'autonomous' or 'self-sufficient' [5].

[3] ZEB has the connection to one or more energy infrastructures, therefore, it has the possibility of both purchasing energy from the grid and feeding in excess energy to the grid to avoid on-site storage and also known as 'net-zero energy' or 'grid integrated' (Ibid).

sources (such as solar power, wind power, hydro power, geothermal energy, biomass) leads to a Net ZEB [19].

While the Net ZEB definition introduced by Sartori et al. (2012), Marszal et al. (2011), and Kolokotsa et al. (2011) has parallels with the definition of the source ZEB introduced by Torcellini et al. (2006), Hernandez and Kenny (2010) introduce *Life Cycle Zero Energy Building* (LC-ZEB) that includes the embodied energy of the building and its components in addition to the annual energy use. LC-ZEB is defined as a building where the primary energy used in the building and the energy embodied within its materials and systems over the lifetime of the building is equal or less than the energy produced by its renewable energy systems within the building over the lifetime of the building [18].

Neighborhood scale

In line with changes in energy systems, the recent literature suggests broadened definitions of a ZEB extended to the neighborhood and district scales. This refutes the notion that a single building is the most effective unit to result in higher energy gains. In this context, district is considered as a larger area that is comprised of neighborhoods. Ala-Juusela et al. (2016) use a similar definition of the concept as in previous studies [5], [19], [20] applying it to a neighborhood scale. The energy demand of a neighborhood includes the energy demand of buildings and other infrastructures, such as waste and water management, parks, open spaces, and public lighting, as well as the energy demand for transport.

Monti et al. (2016) define *Energy Positive Neighborhood* (EPN) as an area that generates more electricity than it consumes. The authors address the key defining features of the future energy systems that include increasing penetration of low carbon electricity production, electric heating, and transport. Given the nature of renewable energy sources (non-schedulable as well as partly non-dispatchable), flexibility is a desired goal that is prioritized at EPNs over being energy positive [23].

Ahlers et al. (2019) propose scaling up from buildings to blocks, and further to a wider scale of neighborhoods and districts with the aim to create climate-friendly and livable urban environments. The authors define a *Positive Energy Block* (PEB) as a set of at least three buildings in proximity that have an average yearly positive energy balance between them [26]. The same definition is provided by Backe et al. (2019). This definition allows to focus on the infrastructure and systems between buildings as part of the built environment. The buildings serve different purposes to optimize local renewable energy production, consumption, and storage. Interaction between PEBs and their neighboring blocks can lead to a *Positive Energy District* (PED), where PEBs become smaller components of the PED [26], [27].

District scale

So far, district-level systems have not received adequate attention. While only a few authors focused on wider areas such as districts in their studies of energy transition [26], [27], [28], [29], the PED concept has gained more attention in policy-oriented works [1], [16].

Jablonska et al. (2012) characterize an *Energy Neutral District* (END) as a district where, on a yearly basis, no net energy import is required from outside the district. ENDs require interaction between a larger group of buildings than in a neighborhood, users and the regional energy, mobility and ICT system in a holistic approach [27]. The interaction of ENDs with their surrounding districts through exporting in case of energy surplus and importing in case of shortage proves ENDs to be efficient [28]. ENDs are considered an integral part of the district energy system and embedded in the spatial, economic, technical, environmental, and social context [26].

PEDs have a similar meaning as ENDs, while energy positivity is an ill-defined term and has an ambiguous connotation [23]. The term “Positive Energy District” is composed of, “Positive Energy” and “District”. First, “Positive Energy” refers to an energy surplus where the (renewable) energy production exceeds the consumption over a certain timeframe [1]. More recently, the extended definition incorporates the environmental aspect, in which “Positive Energy” implies net zero CO_2 emissions through energy generation based on entirely renewable sources [16]. Second, “District” refers to a larger area of the city, which is larger than a block or a neighborhood, as an extension of earlier concepts of PEBs and EPNs.

Lindholm et al. (2021) distinguish three types of PEDs: autonomous, dynamic, and virtual. The difference between these types is their ability to interact with energy networks, consumers, and producers outside their geographical boundaries. While autonomous PED is a district with the energy demand covered by internally generated renewable energy where energy imports are not allowed, dynamic and virtual PEDs are flexible in their interaction beyond the geographical boundaries [29]. The authors highlight that dynamic PEDs imply interaction within the local area, with neighboring areas, and with the energy grid that allows a lot of flexibility in the system, whereas virtual PEDs rely on renewable energy systems and energy storage outside their geographical boundaries. Renewable energy generation systems installed outside the geographical boundaries of PEDs are called virtual power plants[4] (VPPs). VPPs benefit virtual PEDs by enabling them to utilize a larger variety of renewable energy sources and lower costs of energy storage that can extensively contribute to energy flexibility.

[4] A network of decentralized, medium-scale power generating units such as wind farms, solar parks, and Combined Heat and Power (CHP) units, as well as flexible power consumers and storage systems [29].

The goal of EPNs and PEDs is not merely to achieve energy *positivity* [22], but to achieve energy balance – the amount of energy produced is equal to the amount consumed [1]. The reference framework for PEDs (based on national consultation within the EU) outlines three important functions of urban areas in the context of energy systems: *energy production* completely based on renewable energy, *energy efficiency* for best utilization of renewable energy produced, and *energy flexibility* for optimality in the urban energy system [16]. These three functions are defining milestones of PEDs, which are bound to the guiding principles to achieve climate neutrality, social inclusiveness and energy justice, resilience and security of energy supply [16]. The framework suggests energy efficiency to be the priority, as the space needed for the generation of renewable energy is always limited in an urban area.

Table 2. 1. Overview of the definitions from the literature

Concept	Definition	Defining elements				Literature sources
		Geographical boundary	State of interaction with an energy grid	Energy supply method	Balancing period	
Zero Energy Building (ZEB)	*(1) **Net Zero Site Energy Building*** **that produces as much energy as it uses annually when accounted for at the site**, (2) *Net Zero Source Energy Building* that produces at least as much energy as it uses annually, when accounted for at the source, (3) *Net Zero Energy Emissions Building* that produces at least as much emissions-free renewable energy as it uses from emissions-producing energy sources, and (4) *Net Zero Energy Cost Building* that receives as much financial credit for exported energy as it is charged on the utility bills.		Off-grid	On-site	Annual	Torcellini et al. (2006)
Zero Energy Building/Net Zero Energy Building (ZEB/Net ZEB)	*ZEB* is an energy-efficient building able to generate electricity, or other energy carriers, from renewable sources in order to compensate for its energy demand (refers to **autonomous** buildings). *Net ZEB* indicates the **connection to the smart grid**, which enables two-way interaction.	Building	Off-grid/On-grid	On-site/off-site	Annual	Sartori et al. (2012); Marszal et al. (2011); Kolokotsa et al. (2011)
Life cycle Zero Energy Building (LC-ZEB)	*LC-ZEB* is a building where the primary energy used in the building and the energy embodied within its materials and systems **over the lifetime** of the building is equal or less than the energy produced by its renewable energy systems within the building over the lifetime of the building.		Off-grid	On-site	Annual life cycle	Hernandez and Kenny (2010)

Energy Positive Neighborhood (EPN)	*Energy Positive Neighborhood* is an area that **generates more** electricity **than it consumes**.	Neighborhood	Off-grid	On-site	Annual	Ala-Juusela et al. (2016); Monti et al. (2016)
Positive Energy Block (PEB)	*Positive Energy Block* is a set of at least three buildings in close proximity that have an average yearly **positive energy balance** between them.		On-grid	On-site/Off-site	Annual	Ahlers et al. (2019); Backe et al. (2019)
Energy Neutral District (END)	*Energy Neutral District* is a district where, on a yearly basis, **no net energy import** is required from outside the district (refers to self-sufficiency).	District	On-grid	On-site/Off-site	Annual	Jablonska et al. (2012)
Positive Energy District (PED)	*Positive Energy District* is an energy-efficient and energy-flexible urban area or a group of connected buildings, which produces **net-zero** greenhouse gas emissions and actively manages an annual **local or regional** surplus production of renewable energy.		On-grid	On-site/Off-site	Annual	TWG of the European Strategic Energy Technology (2018); JPI Urban Europe / SET Plan Action 3.2 (2020), Lindholm et al. (2021)

Chapter 2

2.3.2. Operationalizing PEDs

Assessment metrics play a significant role in implementing, comparing, and replicating PEDs. Thus, the metrics are expected to reflect the defining elements of the PED concept.

Energy performance within a geographical boundary

A geographical boundary is one of the defining elements of PEDs. However, it can only be characterized qualitatively by a unit (a building, a neighborhood, or a district) that gives an idea of the area size. The areas are treated as a single unit while assessing the scale of energy-efficient areas. Therefore, it is fundamental to specify these units while addressing the metrics.

The other defining elements of the PEDs and overall, the energy performance is assessed within a geographical boundary. Ala-Juusela et al. (2016) and Monti et al. (2016) propose a general set of indicators to assess energy efficiency. More specifically, these indicators relate to energy (energy consumption, generation, efficiency label), economic (energy cost, energy sold to the grid, energy cost savings), and environmental (CO_2 emissions, energy savings) aspects [22], [23]. While these indicators provide a broad scope of energy efficiency, indicators related to contextual and individual factors are still required to contribute to a clearer indication of the PEDs' energy performance.

Interaction with an energy grid

To optimize energy use, two-way communication between buildings and energy grids (smart grids) has become an important element. Different indicators and approaches have been proposed to analyze the building-to-grid interaction [5]. From a building perspective, Sartori et al. (2012) introduce a *grid interaction index*. The grid interaction index represents the variability of the energy flow within a year, where the energy flow is a net export that is defined as a difference between exported and delivered energy within a given time interval [20]. From the viewpoint of a grid, the authors highlight an important characteristic: *grid interaction flexibility*, which allows response to signals from the smart grid such as price signals, and therefore, adjusts load, generation, and storage control [20]. For this purpose, it is meaningful to assess grid interaction flexibility hourly or even with a higher time resolution. Assessing grid interaction flexibility with such a high time resolution is a focus of import/export energy balance calculation and contributes to providing more complete information on the interaction with the smart grid [20]. In contrast, with monthly values that are sufficient to calculate load/generation balance, grid interaction is often overlooked due to focusing only on calculating the loads.

Additionally, Sartori et al. (2012) introduce the weighting system with the aim to convert the physical units of different energy carriers into uniform metrics in order to create common balance metrics. Similarly to the categories of ZEB defined in Torcellini et al. (2006), the authors introduce four types of metrics: site energy, source energy, energy cost, and carbon emissions related to energy use [20]. Within these metrics, they distinguish between symmetric[5] weighting and asymmetric[6] weighting. Different weighting factors can be assigned to different technologies generating the same carrier.

Energy supply method

As one of the defining elements, energy supply gained significant attention in the literature on PED and similar concepts [5], [17]. Torcellini et al. (2006) are one of the first who extensively contributed to the concept of on-site and off-site energy supply. While the on-site supply is distinguished between supply within the building footprint (located on the building) and the building site (located on-site but not on the building), the off-site supply indicates that the building either uses renewable energy sources available off-site to produce energy on-site or purchases off-site renewable energy sources [5]. However, as noted by Marszal et al. (2011), there is ambiguity in renewable energy supply that in some cases is seen as on-site when focusing on the actual location of the energy generation, while in other cases as off-site when focusing on the fuel's origin. Therefore, clear distinctions and definitions of energy supply methods need to be outlined for a common understanding of PEDs.

Balancing period

A balancing period has been heavily discussed in the literature on PED and similar concepts, where the annual energy balance is the most accepted one for calculating the energy balance [5], [22]. To measure the annual balance between local energy supply and demand, Ala-Juusela et al. (2016) designed a set of Key Performance Indicators (KPIs). The foremost KPI, "On-site Energy Ratio (OER)" measures the balance between energy demand and supply from the local renewable energy sources. However, because the OER is generic as it does not consider the time of energy demand and supply (e.g., peak energy demand time) and different types of energy, the authors include additional KPIs[7]. Another option is the sub-yearly balance such as seasonal or monthly [5]. These balancing periods allow energy supply systems to better match the actual energy demand. Nevertheless, it is more challenging to

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[5] The rationale behind symmetric weighting is that the energy exported to grids can avoid an equivalent generation somewhere else in the grid. It is applied to cases when the energy generated on-site does not affect the balance negatively (in terms of costs or emissions), which means the value of the exported energy is equal to the average weighting factor for the grid [20].

[6] The rationale behind the asymmetric approach is that energy demand and supply do not have the same value, which means that delivered and exported energy should be weighted differently in accordance with this principle. It is applied to account for the negative effect of on-site energy generation if that is not accounted for somewhere else in the grid (Ibid).

[7] *Annual Mismatch Ratio (AMR)* measures the amount of energy imported into the neighborhood in the case of each energy type, per year.

Maximum Hourly Surplus (MHSx) measures what is the maximum value on how much bigger the hourly local renewable supply for each energy type is than the demand during that hour, per year.

Maximum Hourly Deficit (MHDx) measures the maximum value of how much bigger the hourly local demand is compared to the local renewable supply during that hour, per year.

Monthly Ratio of Peak hourly demand to Lowest hourly demand (RPLx) measures how big is the peak power demand [22].

achieve zero balance than in the case of annual balance because of the seasonal differences between energy demand and renewable energy generation [5].

Another alternative for the annual energy balance is a life cycle balance, also known as service life of a building [18], [25]. Hernandez and Kenny (2010) argue that the full life cycle of the building (e.g., 50 years[8]) is a more appropriate period to assess the energy balance. Calculations of the life cycle of the building incorporate not only the operating energy use, but also the energy embodied in the building materials, construction, and technical installations and, thus, assess the environmental impact of the building[9] [18]. Similarly, Walker et al. (2018) propose a combined approach of Life Cycle Performance Design and KPIs (LCPD based KPIs) to evaluate the level of sustainability and include the lifetime performance of both buildings and energy infrastructure.

Among the approaches for calculating the annual energy balance, Sartori et al. (2012) suggest using static accounting in order to avoid the complexity of calculations and assumption of time-dependent patterns. However, static accounting does not consider uncertain parameters such as unpredictable use behavior, changing weather conditions, and other time-varying parameters that affect energy efficiency. To limit this uncertainty, dynamic accounting is considered a more suitable approach to measure energy performance as it enables measuring in real-time using smart metering that also allows obtaining energy users' preferences communicated on a daily or hourly basis [19].

2.4. PED practical examples

With a thorough conceptual perspective on PED and similar concepts, zooming in on real-life PEDs can provide additional insights. This section thus presents representative examples of 11 PEDs[10] that have already been implemented in Europe.

2.4.1. Defining elements of the PED practical examples

The selected PEDs are analyzed following the key defining elements identified in the previous section (Table 2. 2). The 11 PEDs are not completely based on renewable energy [32]. While some are more self-sufficient than others, they are still dependent on an additional supply of energy in the low renewable energy supply periods. Thus, they do not

[8] Suggested as a typical value for the service life of buildings when no other data is available [18].

[9] These calculations are expressed through *Annual Energy Use (AEU)*, *Annualized Embodied Energy (AEE)*, and *Annualized Life Cycle Energy (ALCE),* which is a sum of AEU and AEE and gives a life cycle perspective of energy use, where AEU, AEE, and ALCE are expressed in primary energy units per year of service life. At a life cycle ZEB, the ALCE tends to zero, reflecting a true value of efforts to minimize energy use in the built environment (Ibid).

[10] 11 PEDs from Gollner et al. (2019) and Derkenbaeva et al. (2020) fit the scope of this study. Other examples from the list are not considered PEDs because they are not fully PEDs (pilot projects, technology test platforms, PEDs in implementation and planning stage); or projects of private companies that are contributing to PEDs implementation by e.g., providing renewable energy and data-driven technologies (solar panels, smart meters, batteries, etc.).

fully satisfy the definition and are not entirely PEDs but have the goal to follow the path toward it.

While the examples vary in their scales, they are not limited to a district. In fact, PEDs can go beyond the district boundaries and still deliver relatively similar results, especially in the case of islands. Like other energy systems, islands aim at utilizing renewable energy to supply their energy demands. However, by their nature, islands are under higher pressure due to their isolation from the mainland and higher dependence on their natural surroundings [39]. In the case of islands, more efforts are required to achieve the results than in urban areas. Evidently, the PED and similar concepts can be applied to wider scales.

All selected PED examples showcase the interaction with a smart grid. In some cases, the PEDs are largely self-sufficient and involve limited interaction with the energy grid (examples 1, 2, 4, 5, 7, 9), while in other cases, the PEDs generate less own energy and are more dependent on the grid (examples 3, 6, 8, 10, 11). Consequently, the energy supply method in all examples is also characterized as on-site with partial off-site. This means that some of the energy is generated on-site, while some is generated off-site and is imported to meet the energy demand, which shows that none of the 11 PED examples is autonomous, but rather are dynamic PEDs. Moreover, for a significant share of the building stock, especially in densely populated urban areas, plus-energy standard or Net ZEB standard is not practical for the near future with current technologies, system boundaries, and economic incentives [40]. Hence, the existing PEDs do not provide “proof-of-concept”.

Table 2. 2. Overview of the PED examples in Europe

№	***PED example***	***Defining elements***		
		Geographical boundary	***State of interaction with an energy grid***	***Energy supply method***
1	Schoonschip, the Netherlands	Neighborhood	On-grid (smart), one connection to the energy network	On-site (+passive off-site)
2	Aardehuizen, the Netherlands		On-grid (largely self-sufficient)	On-site (+passive off-site)
3	Hunziker Areal, Switzerland	District	On-grid	On-site/Off-site
4	District of Vauban, Germany		On-grid (largely self-sufficient)	On-site (+passive off-site)
5	La Fleuriaye West (Carquefou), France		On-grid (largely self-sufficient)	On-site (+passive off-site)
6	IssyGrid/ Fort d’Issy, France		On-grid (smart)	On-site/off-site
7	Samsø Island, Denmark	Island	On-grid (largely self-sufficient)	On-site (+passive off-site)

8	The Orkney Islands, the UK		On-grid	On-site/off-site
9	Isle of Eigg, the UK		On-grid (largely self-sufficient)	On-site (+passive off-site)
10	The Åland Islands, Finland		On-grid	On-site/off-site
11	Goeree-Overflakkee Island, the Netherlands		On-grid	On-site/off-site

Note: The information on the selected PED examples' balancing period is not available. There is also a lack of information on how the energy performance of these PEDs is assessed.

2.4.2. Extended overview of the PED practical examples

As can be observed, the examples based on the key defining elements fall short of providing a complete picture of the PEDs. Thus, to gain a better understanding of the PEDs in practice, a more comprehensive overview is needed.

PEDs are designed as an integral part of the district energy system and subject to be intrinsically scalable up to districts and cities and are embedded in the spatial, economic, technological, environmental, and social context [26]. This means PEDs depend on their contextual factors, and therefore, differ based on them (Table 2. 3) [31], [32], [33], [34], [35], [36], [37], [38], [39]. Figure 2. 2 offers a visualization of the different geographic scales and contextual factors of real-life PEDs in residential areas.

Table 2. 3. Extended overview of the PED examples

№	PED example	Geographical boundary	Contextual factors				
			Spatial	***Technological***	***Economic***	***Environmental***	***Social***
1	Schoonschip, the Netherlands	Neighborhood	Newly built 46 homes (100 residents)	Solar panels, heat pumps, storage batteries	Own investments	Self-sufficient based on RE, climate neutral	Initiated by the citizens, cooperation with the municipality and other partners
2	Aardehuizen, the Netherlands		Newly built 23 homes	Solar panels, thermal mass, heat pumps	Own investments	Ecological area with self-sufficient earth houses	Initiated by the citizens, cooperation with the municipality and regional experts
3	Hunziker Areal, Switzerland	District	Newly built 13 buildings (1300 residents)	District heating based on warm exhaust air, rooftop solar panels, and smart energy optimization platforms	Saving up to 30% of annual heating costs; revenue from the energy sales	Reduce energy consumption, CO_2 emissions	Collaboration of residents (cooperative members), the municipality, architects, neighbors
4	District of Vauban, Germany		Newly built 2000 homes (5100 residents)	Solar panels, district heating, passive housing	Reduced energy costs, revenue from the energy sales	Self-sufficient based on RE, reduced emissions, sustainable mobility	Initiated by the citizens, supported by the city
5	La Fleuriaye West (Carquefou), France		Newly built district, 600 homes (320 delivered, 300 by 2022)	Solar panels, biomass, passive housing	Shared investments by partners, reduced energy costs	Self-sufficient based on RE	Initiated by the city, collaboration with 18 partners
6	IssyGrid/ Fort d'Issy, France		1600 homes	Solar panels, smart grid, meters, storage batteries	Shared investments by partnering companies, revenue from energy sales	Reduced emissions	Initiated by private property developer, collaboration with other private partners

7	Samsø Island, Denmark		3724 residents	Wind turbines, solar panels, biomass	70% of the investments came from local investors and residents, revenue from the energy sales, annual financial returns from investments, subsidies of up to 30% for renewable energy technologies installations and energy efficiency refurbishments	Self-sufficient based on RE, recycling of waste, sustainable mobility	Initiated by the citizens, cooperation with the municipality, local energy agency, the local development office and the municipally owned energy company
8	The Orkney Islands, the UK	Island	22000 residents	Wind turbines	Revenue from energy sales	Self-sufficient based on RE	Initiated by the local community
9	Isle of Eigg, the UK		96 residents	Hydroelectric plants, wind turbines, solar panels, storage batteries	EU funding, islanders' investment, a bank loan, reduced energy costs	Self-sufficiency based on renewable energy sources	Initiated by the citizens
10	The Åland Islands, Finland		3000 residents	Solar panels, wind turbines, wave and geothermal energy, storage batteries	Public – private – people partnership	Self-sufficiency based on renewable energy sources	Collaboration of citizens, the municipality, private stakeholders, research organizations
11	Goeree-Overflakkee Island, the Netherlands		Half of the island (22 000 households)	Wind turbines, solar panels	Local investments, receiving a yearly revenue of 6% from the dividends	Self-sufficiency based on renewable energy	Initiated by the citizens

With the priority of energy transition to tackle challenges such as climate change and energy poverty, PEDs mainly pursue environmental and social goals. Environmental goals are focused on combating climate change and decreasing dependence on fossil fuels by reducing CO_2 emissions, using sustainable mobility, and becoming self-sufficient based on renewable energy (RE). These targets are central and consistent across all examples. Another prevailing effort of PEDs is to reduce energy poverty. This social goal includes reducing energy bills, making energy available and affordable for all groups of end-users, and creating a livable and safe environment. Together, environmental and social goals require actions from different groups of stakeholders, their initiative, and collaboration. Clearly, the 11 PEDs demonstrate the importance of these ingredients that have contributed to an acceleration of the energy transition, showcasing initiative and strong engagement of citizens as well as collaboration with other stakeholders making PEDs possible [32].

Despite their similar goals, the contextual factors are different and demand distinct approaches in achieving the PED goals [32], [41]. One of the contextual factors that play a role in PED implementation is spatial. Spatial features may include geographic characteristics such as a physical scale of an area (e.g., neighborhood, district, city, region) or non-geographic – area type (e.g., residential, industrial, business district), and building type (newly built/existing). Among the 11 examples, there are residential areas with newly constructed buildings (examples 1-5) including those built on wastelands (example 3) and in old industrial districts (example 1) and residential areas with already existing buildings (examples 6-10). Additionally, geographic characteristics include climate conditions that are characterized by temperature, precipitation, and wind [4], but also include, inter alia, latitude, elevation, topography, distance from/to the ocean, location on a continent. Altogether, these spatial features play a role in designing different pathways toward implementing PEDs.

These spatial features are an important aspect for applying suitable technological solutions. For example, PEDs that have larger scales and are in the northern part of the region (examples 7-11) generate their energy using wind, while PEDs at a smaller scale and located closer to the south (examples 1-6) tend to generate their energy using solar and heat energy. Also, technological solutions depend on existing energy infrastructure. Energy infrastructure encompasses numerous components such as generation, transmission, and distribution of energy, physical networks of pipelines, and other transportation elements [42]. Depending on these infrastructural characteristics, suitable technologies or a combination of technologies can be installed. As seen in all 11 PEDs, a combination of technologies is more effective for the energy system based on renewable energy due to its fluctuating nature and allows PEDs to achieve efficiency and flexibility [32].

To implement technological solutions including technology purchase and installation, adequate funding is required as PEDs are more expensive than traditional projects. The main source of financing usually comes from the partnership of several stakeholders including local citizens, municipalities, and private companies. While in most of the examples the investments in technological solutions were made with the environmental and social goals, two PEDs (examples 6 and 8), seen as opportunity-driven, invested primarily pursuing an economic goal – to create revenue from energy sales. Nevertheless, all PEDs have gained different economic benefits such as dividends from their investments, reduced energy costs and savings, and revenue from energy sales to the grid.

Another contextual factor is environmental. Environmental factors include pollutants and temperature, where pollutants cause air/environment contamination and temperature rises to various extents. This creates different environmental contexts in different localities. Therefore, the environmental factors also determine what techno-economic solutions should be implemented.

Finally, social factors were fundamental for the stakeholders in the 11 PEDs to take actions such as vis-à-vis initiating the PEDs and collaborating to implement them. These factors vary significantly as they include culturally related features, inter alia, identity, trust, power relations, sense of community. While some PEDs (examples 1-4 and 7-11) are initiated bottom-up, others (examples 5 and 6) are initiated top-down.

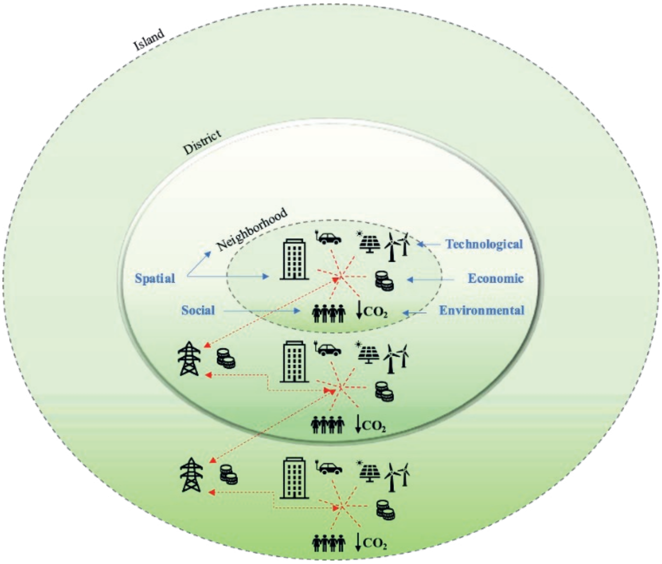

Figure 2. 2. Real-life PEDs in residential areas

2.5. Comprehensive view on PEDs

The proliferation of studies with diverse definitions of PEDs together with the growing number of PEDs in practice calls for the development of a practicable yet comprehensive view on the concept.

2.5.1. PEDs as resilient complex adaptive systems

Complex adaptive systems framework

Complex adaptive systems (CAS) is a powerful framework for studying dynamics and resilience [6]. As the name suggests, CAS is a complex system that consists of dynamic network of interactions of its components, and it is adaptive as it adjusts to the changing environment. The CAS components are able to organize autonomously following a set of rules. Their complex (micro) behaviors create non-linear dynamics due to new or changing interactions, based on which macro nature of the system emerges [6]. Additionally, the macro nature of the system is profoundly dependent on the past decisions and behaviors that have led the evolution of the system in particular directions. Importantly, the complexity of the system is also characterized by interaction of sub-systems (e.g., technologies, institutions, business models, etc.) that mutually coevolve and complement each other.

Evidently, the main properties of CAS include components, networks, dynamics, self-organization, path dependency, emergence, co-evolution, learning and adaptation [30]. All these characteristics formulate the paradigm of CAS. Central to CAS is that any element of the system cannot be understood separately, but must be defined holistically as a system of components and their interactions. The multidisciplinary nature of this phenomenon allows applying CAS to a wide variety of research domains.

PEDs as complex adaptive energy systems

The energy transition requires substantial energy efficiency measures, urgent adoption of innovative technologies, policies and regulations, and financial investments that are rather uncertain. This process is driven by heterogeneous agents of energy systems such as end-users, companies, regulators, and governments, sometimes with conflicting interests. These agents and technologies interact through physical and social networks governed by institutional structures creating the environment wherein the energy systems operate [30]. Their interaction changes over time according to dynamic rules, which emerge with the availability of new technologies, policies, and decision-making processes. Together, these elements make energy systems examples of complex systems. This is well demonstrated by the practical examples of PEDs that incorporate these elements. However, the existing PED and similar concepts are less comprehensive and do not mirror this complexity.

Complex systems are adaptive insofar as they have the capacity to change under the influence of social, physical, and other factors of the environment (e.g., political, economic). Thus, energy systems are CAS incorporating heterogeneous elements (agents and technologies) that interact and create impacts on other parts of the system [30]. Hence, if one wishes to understand their function, these components must be considered within the system. The practical advancement of PEDs demonstrates the complexity of energy systems by the interrelations of the spatial, techno-economic, social, and environmental aspects, which can be referred to as sub-systems. All these aspects forming a comprehensive overview of PEDs are essential to develop pathways toward the Vision 2050 (Figure 2. 3). The Vision comprises the aim of the EU to be climate-neutral by 2050 that is at the heart of the European Green Deal, and is in line with the EU's commitment to global climate action under the Paris Agreement [43].

As the most densely populated, urban areas experience space constraints. Finding a suitable location for energy infrastructure installations has become a serious challenge. By their nature, renewable energy-related technologies (such as solar panels, wind turbines, heat pumps, energy storage batteries, etc.) demand ample space to be installed. Identifying building or district spatial capacity will be key for solving a technical part of the energy transition. Another point to consider is climate conditions, which matters for finding suitable renewable energy technologies that can be utilized at full capacity.

Considering the complexity of energy systems, a combination of different technological solutions will be essential, which highly depends on the spatial features of the area. The implementation of technological solutions, such as installation of smart energy technologies and refurbishment of a built environment, requires extensive investments [44]. With these, efficient and economically feasible technological solutions take a pivotal role in an energy system's transition towards an increased share of renewable energies. The technological and economic factors come together in energy system transformation, as they guide the directions of possible PED pathways depending on technologies required and investments available.

However, significant investments required for the energy transition (especially, in economically poor areas) may contribute to an increase in energy poverty and in disparities between different income groups of end-users [14]. Therefore, in order to preserve the balance in wealthy and impoverished areas, a combination of targeted policies is important. More specifically, technological solutions must be accompanied by policies that financially allow their implementation in all parts of society. The complementarity of sub-systems (technologies-institutions) can allow the balance in the energy transition in diverse areas. As such, the affordability of the energy transition should be considered in developing solutions for PED implementation.

Energy system transformation is only feasible with the presence of the social aspect that, in this study, refers to interactions of individuals based on their norms and values. Social dynamics are complex in the sense that they are dependent on socio-cultural context and socio-psychological context [45] and increasingly important for the modern energy systems while they drive the path to PEDs [32]. These contexts incorporate social identity, trust-building, and power relations. They deserve more attention in understanding the social system but have been underestimated and simplified in energy transition studies [45]. In practice, it can be observed, that most of the representative examples of PEDs are initiated and led by the citizens that demonstrate a bottom-up approach where social identity, trust-building, and power relations played a fundamental role.

In the energy transition, the key role is played by the end-users [46] as they are the stakeholders for whom this transition is primarily being held, who will make decisions and act based on their motives and social-value orientations. Thus, their roles and behavioral patterns are central for developing energy transition accordingly. In regulating the energy transition, the governments and policymakers take the leading role.

Altogether, the PED concept has been developed to mitigate environmental challenges such as climate change and CO_2 emissions. With the purpose to reduce CO_2 emissions, the PED concept focuses entirely on renewable energy generation. To eliminate dependence on fossil fuels, a combination of spatial, techno-economic, and social solutions should be developed where a central mission is CO_2 emissions reduction [47].

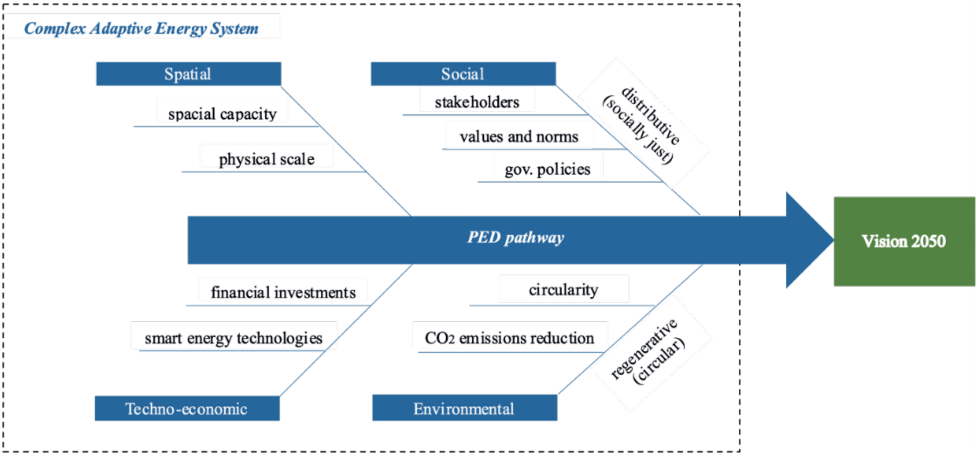

Figure 2. 3. Doughnut pathway toward the vision

Doughnut Economics view on PEDs

As PEDs focus on the environmental and social goals, they are well aligned with the view of Doughnut Economics (or Doughnut for short). This framework proposes viewing the system we are living in holistically pursuing two goals: (1) to not exceed the ecological ceiling by exhausting the natural resources, and (2) to ensure that everyone's needs are met by creating socially just space for humanity [7]. This innovative model is based on the coherence between economic policy, environmental and social issues assuming that agents' actions are interconnected [48]. Therefore, the integration of the Doughnut vision into CAS can contribute to achieving the goals of PEDs.

When applying the Doughnut to the energy domain, the main social foundation to consider is access to energy, while the ecological ceilings are climate change and air pollution. As such, the PED Doughnut is the safe zone between these two extremes, which represents the ability to thrive economically. In order to remain in this PED ring framed with the Doughnut boundaries, the focus must be on basic principles such as reducing, reusing and producing. More specifically, reducing energy consumption based on fossil fuels and reusing are efforts to reduce CO_2 and avoid environmental degradation, while producing renewable energy and redistributing it are efforts to create access to clean energy for all and allow social inclusion and energy justice.

Importantly, Doughnut Economics has been developed with the focus on *distributive* (i.e., sharing with others the value created and redistribute it to improve equity amongst the users) and *regenerative* (i.e., promoting circularity of resources) dynamics. These dynamics are central for energy systems to tackle challenges and shift from unsustainable to (more) sustainable. PEDs can be exposed to disruptions, whether due to climate change, COVID-19, or renewable energy-related issues. Designing resilient systems is crucial for a successful energy transition where the system can not only be resistant to disruptions and can quickly restore after a disturbance [49], but also ensures socially just space. Hence, robustness should be comprised in the PED concept with the capacity of the energy system to tolerate disturbances while retaining its functions. This can be achieved through adaptability or transformability of the system: by adapting to the new circumstances preserving its basic features or by transforming to a new state creating new mechanisms to respond to disruptions [49].

Nevertheless, the understanding and application of the Doughnut framework in energy transition research and policy domains is still in an early stage. There are no studies that have applied this vision for the PEDs pathway. One of the frontrunners in the implementation of Doughnut Economics on a local level is Amsterdam [50]. However, its main emphasis is solely on circular economy. Thus, Figure 2. 3 illustrating CAS is intended as a call for further studies to pay more attention to incorporating the Doughnut view into the PED concept.

2.5.2. Discussion of the PED concept's limitations and future research directions

This comprehensive view on PEDs includes new lenses such as the complexity of the system and the Doughnut approach, through which PED implementation can be viewed and guided. These novel ways of approaching the energy transition bring comprehensiveness and resilience of PEDs into focus. Nevertheless, there are several limitations in the PED concept that merit more attention, and their integration can contribute to achieving far-reaching PEDs.

One of these is technologies' after-lifetime emissions. Technologies used for generating and storing renewable energy such as photovoltaic solar panels, wind turbines, and energy storage batteries are not completely renewable, since they create a negative environmental impact after their lifetime (average 25-30 years – solar panels and wind turbines, 10-20 years – energy storage batteries) [51]. Additionally, the mining of minerals for lithium-ion batteries also contributes to environmental degradation and this impact spreads beyond the area they are used in. However, the impact is still minor when compared to that of fossil fuel-based energy. Most components of these technologies are recycled or reused (approximately 90%) [52]. Even though the negative environmental impact of renewable energy technologies is relatively insignificant, the emissions produced should be taken into account in assessment metrics to cover the full life cycle of PEDs.

Furthermore, the existing PED concept does not include electric mobility and its energy demands, which remains an important knowledge gap. Electric mobility has been recognized as one of the solutions for mobility transitioning to renewables. By its nature, electric mobility creates two main benefits: (1) it contributes to the reduction in CO_2 emissions, and (2) it emerges as energy storage [53]. As energy-consuming technologies, electric vehicles (EV) create additional electricity demand. This means that more electricity should be generated in order to satisfy this demand. However, despite an increase in electricity demand, emissions can still be reduced if there is a substantial change in energy infrastructure. Another function of electric mobility, energy storage, can boost the flexibility of the energy system and stability of the grid by shaving the peaks of power. EV storage batteries enable to store and reuse the energy that is generated when the demand is low [54]. It means that a significant electricity storage capacity would be available with all these batteries on wheels [55]. However, infrastructure-related issues such as the installation of more smart charging points for EVs remain a concern. Given the expected rise of electric mobility and PEDs, more research on these issues is imperative.

Zooming in on the real-life PEDs, these are clearly path dependent. While sharing some similarities such as energy self-sufficiency, social cohesion, reliance on a combination of innovative technologies, a partnership of stakeholders, and created sustainability values, the PED examples reveal significant differences [31], [32]. First, they vary in their geographical scale –a neighborhood, a district, an island. This demonstrates that a PED should not be tied to the term “district” and restricted to this unit, but rather should be flexible in delineating the scale as long as it satisfies the requirements of the PED concept and allows to create PEDs in a different (smaller or larger) geographical scale. Second, the PEDs differ in their targeted stakeholders and contextual factors. Targeted stakeholders of the given examples vary from end-users (who later become prosumers[11]) to social housing cooperatives and residents (tenants). Contextual factors such as built or newly built buildings, available renewable energy sources, required financial investments, awareness of citizens and readiness for technology adoption, local policies and regulations make the PED examples distinctive. Evidently, there is no one-size-fits-all solution for the implementation and replication of PEDs.

[11] Energy users who generate renewable energy in their domestic environment and either store the surplus energy for future use or trade with interested energy customers in the smart grid [56].

Accordingly, the future research directions of PEDs should include the following:

- Incorporating the Doughnut view into the PED concept with the aim to comprise the full life cycle of the energy system with regenerative and distributive dynamics of resources that contributes to resilience of the system.
- Investigating electric mobility, as it is a promising but underdeveloped area related to energy transition and PEDs with high potential to contribute to carbon emissions reduction and providing (additional) portable energy storage.
- Applying a bottom-up approach in studying PEDs, as they are flexible in delineating the physical scale and have a better chance to be implemented locally first, and then have an impact globally.

2.6. Conclusion

Reviewing the PED and similar concepts and comparing them to the real-life PEDs reveal substantial knowledge gaps and limitations of the concepts. First, there is a lack of consistency between PED and similar definitions and concepts that often causes misinterpretations. Inconsistency also occurs in the assessment metrics across the existing PED-related concepts. Second, being too simplistic, the concepts fail to consider the contextual factors that are inherent in the real-life PEDs. Contextual factors make PEDs path dependent and can explain deviations. This also means that there is no one-size-fits-all solution for PEDs. Third, energy flexibility can only be achieved through dynamic and virtual PEDs, and hardly through autonomous ones. The existing concepts are too idealistic and ambitious in constructing the image of PEDs as autonomous, and they fail to consider the features of modern urban areas such as high population density, space scarcity, and limited availability of renewable energy. Therefore, the extended interaction of PEDs with the neighboring districts or virtual power plants, which makes PEDs dynamic or virtual, is more successful in achieving flexibility as observed in the practical examples of PEDs. Fourth, the assessment of the technologies' after-lifetime emissions is not included in the PED metrics. As the technologies are not completely renewable, even though their emissions are relatively insignificant, this is a knowledge gap that is essential to be considered to cover a full life cycle of PEDs.

This study significantly contributes to the literature, as it has developed a comprehensive view on the PED concept and integrated the CAS and Doughnut Economics views into PEDs. This has not been previously explored, though it can be essential to boost the local energy transition since these two frameworks enrich the PED concept by comprising the complexity and resilience of PEDs. A necessary route for future research is electric mobility that should be studied more extensively and included in the PED concept, as it can contribute to solving a pressing problem of energy storage. Another promising direction for future studies is integrating the Doughnut view into the energy transition and specifically PEDs. The application of this view in PEDs can contribute to a desired future energy system that is climate-neutral and resilient by incorporating regenerative and distributive dynamics.

Policy recommendations for future development of PEDs include the following:

- PEDs should be developed using area-based approaches that aim to include all groups of end-users and diverse areas. The area-based approach means allowing different combinations of policies that would target specific groups in PEDs development taking into account their local (spatial) contexts. Specifically, the policies should have two main branches – financial and social. While the first branch addresses the financial leverage in energy transition such as imposing taxes (suitable for wealthier regions) or offering subsidies and loans (targeting more impoverished regions), the second branch shall focus on encouraging local energy initiatives and supporting collaborations (e.g., through organizing information campaigns, creating knowledge exchange platforms). Socially-oriented policies are important, as initiative and collaboration of different stakeholders have been proven by the examples to be fundamental in developing successful PEDs.
- Emphasis should be given to electric mobility and its benefits. However, there are also (financial) challenges in transformation to electric mobility. Therefore, in order to make the transformation smoother, the policies shall target (especially) vulnerable groups through providing alternatives or supportive conditions that would allow affordability and inclusion.
- Development of dynamic and virtual PEDs should be prioritized over autonomous ones especially in modern urban areas that face challenges such as high population density, space scarcity, and limited availability of renewable energy. The dynamic and virtual PEDs allow flexibility through interacting with neighboring PEDs and VPPs. As observed in the practical examples, this can lead to successful implementation and sustainability of PEDs.

3

Chapter 3

Who invests in energy retrofits? Mining Dutch homeowners' data

This chapter is based on: E. Derkenbaeva, A. Akhatova, E. van Leeuwen, L. Kranzl, S. Halleck Vega, G.J. Hofstede, "Who invests in energy retrofits? Mining Dutch homeowners' data," *Energy Policy*, 2023 (under review).

Abstract

As climate change and energy crises become more pressing, understanding the factors affecting households' decisions on energy-efficient retrofitting (EER) is essential for designing effective policies. The analysis of the data from the Netherlands through principal component analysis and binary logistic regression reveals valuable insights. Older and smaller households of which the inhabitants have owned and lived in their residences for a long time are less likely to adopt heat pumps or invest in solar panels and insulation. To address this, the government should provide financial and technical support for the elderly to increase energy efficiency in their homes. On the other hand, homeowners who actively participate in neighborhood cohesion are more likely to invest in solar panels and insulation. Neighbors' active engagement can mean information exchange and support for EER adoption. Therefore, community support and information are key to increasing energy efficiency and sustainability, and governments should offer awareness campaigns and make information more accessible. Supporting bottom-up neighborhood initiatives with technical and financial assistance and streamlined regulations is also crucial. These insights on elderly support and the neighborhood effect can also inform energy policies in other countries.

3.1. Introduction

The need for energy-efficient retrofitting (EER) in buildings has become increasingly pressing, driven by the urgency to reduce energy consumption, curb carbon emissions, and combat climate change, as well as address the recent gas import shortages in Europe. The residential buildings sector is particularly important in this regard, as it is responsible for significant energy consumption and greenhouse gas emissions. One key strategy for improving energy efficiency in the residential buildings sector is energy-efficient retrofitting of buildings in the owner-occupied sector, constituting 70.1% of the total housing stock in 2021 [57]. EER includes measures such as insulation of windows, roof, walls, and floor, as well as the adoption of heat pumps or solar panels (i.e., photovoltaic (PV) systems). These measures are essential, especially in colder climates where heating constitutes a large share of the energy demand supplied by fossil sources [58]. In the Netherlands, the need for EER is particularly urgent as residential buildings accounted for approximately 14% of total greenhouse gas (GHG) emissions in the country in 2020 [59]. This is due to a prevalence of old and inefficient buildings[12] and a high dependence on individual gas boilers [2], [60].

Several policies in place aim to encourage homeowners to improve the energy efficiency of their dwellings. One of the most entrenched policies so far is the Energy Performance Certificate (EPC) (locally known as "energielabel"), which requires homeowners to provide buyers or renters of an apartment with its energy efficiency status [61]. Though the obligatory renovation of worst-performing buildings has been shortly introduced with the Minimum Energy Performance Standards (MEPS) as part of the EPBD recast [62]. Currently, the Dutch government has not set the minimum energy label and considers no punitive measures for non-abiders[13]. A number of fiscal policy measures targeting homeowners are present: a higher tax on gas and a lower tax on electricity; Value Added Tax (VAT) refund for solar panels; VAT reduction for insulation materials; investment subsidy for sustainable installations such as heat pumps; low-interest rate loans for EER such as insulation, heat pumps, and solar panels [63]. New approaches have been implemented recently, such as an online advisory tool for homeowners [64] and the "Renovation accelerator" for housing associations to bundle their EER demand [65]. Also, together with residents and building owners, local municipalities are developing sustainable heat and power solutions for each district (heat networks, heat pumps, fully electric or otherwise) and gas-free neighborhood pilots and testing grounds [66].

Despite the presence of several policies aimed at promoting energy efficiency in residential constructions, there is still significant potential for improvement, particularly in the areas of floor and facade insulation [3]. Additionally, a large number of homes in the Netherlands

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[12] Residential buildings built before 1940 constitute 1.6 million out of the 8 million total dwellings.

[13] Homeowners are required to have energy labels upon selling or renting a residence. However, in the residential sector, there is no minimum permissible level. On the contrary, office buildings must have at least energy label C as of January 1, 2023 [200].

have an energy label of C or lower, indicating inadequate insulation that can hinder the effectiveness of heat pumps [3]. The Netherlands Environmental Agency estimates that current policies are not sufficient to reach the goal of the Green Deal to reduce carbon emissions by 55% by 2030 compared to 1990 levels [60]. While evaluating the effectiveness of the introduced policies is challenging, and it will take time for the them to take effect, further understanding of what drives and hinders homeowners' EER investment decisions will help to better align policies and programs with homeowner needs and priorities.

Hence, in this study, we examine further the factors associated with homeowners' investment decisions focusing on four EER measures including window double-glazing, roof, walls, and floor insulation, solar panels, and installation of heat pumps. The literature highlights the complexity of such decisions and indicates that they are associated with many different factors [67], [68], [69], [70], [71], [72], [73]. One important set of factors constitutes the physical characteristics of a dwelling, such as type, age, and size of dwellings [74], [75], [76]. Socio-economic and demographic factors such as household size, income, age, and education are also often studied [71], [73], [76]. However, the findings on their association with geography and energy efficiency decisions are inconsistent and contextual (i.e., they might differ based on geographic area or type of EER). On the other hand, motivational factors such as the necessity to renovate and improve comfort exhibit more consistency across studies, thereby shedding light on why people choose to renovate [69], [77], [78], [79]. Thus, further research is needed to better understand the relationships between factors in order to contribute valuable policy implications for the Dutch energy transition.

In this regard, the contribution of this article to EER-related research is manifold. First, we use the latest release of the Dutch Housing Survey WoON from 2021[14] [80] which enables us better understand the predictors of EER adoption in the past five years in the Netherlands. It ships with a wider variety of variables, including heat pump installation as one of the EER measures, which was not part of the previous releases and has not been studied before. Second, we develop a more comprehensive overview of the predictors of EER adoption decisions via a systematic literature review. Third, we conduct a principal component analysis (PCA) to reduce the dimensionality of the predictors by combining them into components and to understand how different variables are related. Furthermore, we conduct a logistic regression analysis on the derived components to uncover their relationship with EER adoption. Finally, the combination of these three methods (systematic literature review, PCA, regression) offers a viable approach to synthesize evidence-based recommendations useful for further calibration of the policies encouraging the uptake of EER in the country. The insights of this study can also be useful more widely for energy policy frameworks in other countries.

[14] The newest survey release became available in 2022.

The remainder of the article is organized as follows. Section 3.2 summarizes the findings of the previous literature pertaining to relevant explanatory variables. Section 3.3 presents the data and the methodology used for investigating the relationship between the predictors of EER adoptions. The results and discussions are addressed in Section 3.4. Finally, the article concludes by summarizing the key insights of the study and their policy implications in Section 3.5.

3.2. Systematic literature review

There is a large body of literature on factors supporting or hindering the adoption of EER [68], [69], [73]. In this study, we focus on the literature based on quantitative surveys. Thus, we conduct a systematic literature review on survey-based papers to distill the determinants of owner-occupiers' EER investment decisions. We consider measures such as improving the thermal performance of the building envelope (e.g., double and/or triple glazing windows, insulation of façade, attic, floor), switching to sustainable heating, such as heat pump or solar thermal, and adopting residential solar panels. Both general terms (e.g., "renovation", "retrofit", and "refurbishment") and specific measures (e.g., insulation, heat pumps, etc.) are included in the search term below. In relevant empirical studies, the terms "factor", "explanatory factor", "determinant", and "predictor" are usually used interchangeably [73]. Moreover, we are interested in homeowners' decisions to "adopt", "invest" or "implement" EER measures. Thus, relevant synonyms of these actions are used in the search string.

Initial search string[15]:

TITLE-ABS-KEY (energy AND (renovation OR retrofit OR refurbishment OR efficient OR insulation OR "double glazing" OR "triple glazing" OR renewable OR solar OR photovoltaic OR pv OR "heat pump") AND (factor OR determinant OR explanatory OR predictor) AND (adoption OR uptake OR purchase OR implement OR install OR perform OR undertake OR invest*) AND (homeowner OR owner OR owner-occupier))*

The search was conducted in the Scopus database on November 28, 2022. A total of 461 records were found. Several studies are excluded based on the following criteria:

- Publication type and language: only scientific articles published in peer-reviewed journals and written in English (160 articles);
- Discipline: studies from journals irrelevant to energy studies (e.g., articles from the journals such as Maritime by Holland, Physical Chemistry Chemical Physics) (127 articles);

[15] Some search terms are in quotation marks which helps to search for specific collocations, e.g., "heat pumps" and not for "heat" and "pumps" separately. Asterisk (*) is used to search for terms with varying endings, e.g., efficient* searches for "efficient" and "efficiency".

- Topic and method: other housing sectors than residential households owned and occupied by the same entity (i.e., owner-occupiers); measures not included in the EER defined above; qualitative methods, e.g., interview-based or purely theoretical articles (105 articles);
- Context: studies from regions other than Europe, e.g., China and the Middle East, are excluded as they have very different backgrounds and goals (40 articles).

The final set of 29 articles (Figure 3. 1) is reviewed to determine which factors affect homeowners' decisions to adopt retrofitting or one or more of the specific retrofitting measures. Studies that only measure socio-psychological determinants, such as social values, were not included, as they are outside this study's scope.

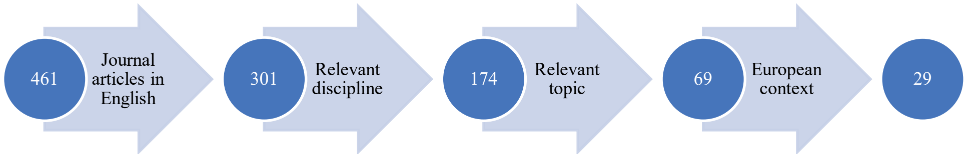

Figure 3. 1. Systematic literature review: screening of relevant studies

A summary of the renovation measures considered across the 29 articles is presented in Figure 3. 2. Four articles study energy renovations in general and do not focus on particular measures [74], [81], [82], [83]. Nine studies examined more than one type of EER. The rest of the studies focuses on a single type of EER: one study on solar panels [84], one study on energy-efficient windows [85], five studies on insulation, and nine studies on sustainable heating choices. There is a slight overrepresentation of studies investigating sustainable heating choices (i.e., heat pumps, wood pellet heating, solar thermal as a replacement [86], supplementary [87], or hybrid heating system [88]). Four studies are focused on the Netherlands. The description of selected articles and the transparent screening process are provided in the supplementary material.

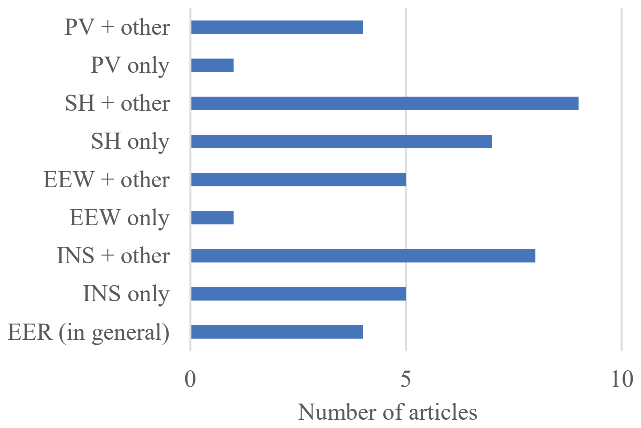

Figure 3. 2. Description of the selected articles (PV = photovoltaic panels, SH = sustainable heating, EEW = energy-efficient windows, INS = thermal insulation of building envelope, EER = energy renovation) from the time period between 2010-2022

3.2.1. Socio-demographic variables

Homeowners' *age* is one of the often studied variables in examining decisions on EER [73], [89], with contradictory conclusions. Most of the reviewed articles report in a negative relationship; that is, the older the homeowners are, the less likely they are to adopt EER [70], [82], [87], [90], [91], [92], [93]. 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 [70], install EEW [70], [94], and invest in sustainable heating (pellet, heat pump, etc.) [95]. 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 [96], whereas in Sweden and the Netherlands, middle-aged groups are more likely to insulate [76], [79] or install PV [76], [84].

Similarly, homeowner's *income* demonstrates mixed outcomes. In all observed studies, income shows a positive correlation with decisions to insulate [70], [96], [97], install EEW [70], [97], adopt a more sustainable heating system (e.g., ground heating [88], or install a heat pump [88], [92], [95]. 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 [94] and thermal insulation in rural Poland [92], 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 [76], [79], [90], [98], to install heat pumps [92] or solar panels [76], [94] or EEW [76]. Education level of a homeowner is negatively correlated only with adopting wood pellet heating [87], [88], [92], [99]. Ruokamo (2016) suggests it could be due to the high maintenance needed for this type of heating [88].

Regarding *family composition*, couples with children are most likely to invest in EER [94], [100]. This may be correlated with *household size* (i.e., the number of people in a household), as Groot 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 [70]. However, results from Poland indicate that the likelihood to insulate decreases as a number of people in the household increases [98].

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 [82], [83]. It holds in the case of EEW installation [70], [85], insulation [70], and solar panel purchase [76]. 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 [69], [101].

3.2.2. Dwelling characteristics

Building age positively correlates with renovating decisions [82], [83]. It is especially evident for insulation and replacing windows with more energy-efficient ones [90], [97], [102]. Heat pumps are installed in newer houses [92]. For solar panels, the adoption rate decreased with the house age; most adoptions occurred in homes built after 2000 [84]. 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 [76], [94], [100].

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 [70], [76], [84], [94], [97], [100], [103].

Home size, or *surface area*, also shows mostly a positive relationship, as larger houses are more likely to install heat pumps [92] and other sustainable heating systems [87], insulation [98] and PV [84]. 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 [87], [94], [98], [102]. However, if the heating system is relatively new (i.e., after 2000), homeowners are not considering installing a different heating system [90]. In addition, Ameli and Brandt (2015) find that homeowners who perform low-cost conservation measures are more likely to invest in renewables or EER [70].

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 [79]. Stockholm county and North-Central Sweden were less likely to insulate compared to other parts of the country [79]. In Germany, east Germans are more likely to insulate [90] and install heat pumps [92], while the south of Germany has a low probability of choosing heat pump but a high probability to choose pellet heating [92].

Several articles relate this difference in adoptions to the *level of urbanization*. 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 [76]. Michelsen and Madlener (2012) also found that rural areas have a lower likelihood of adopting heat pumps [92]. Trotta (2018) 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 [100]. 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" [100].

3.2.3. 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 [94]. 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 [85]. 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 [76], [90].

Improved comfort is one of the essential motivations for renovation [94], 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 [77], [78], [79]. Moreover, the belief that measures improved comfort is an essential predictor of undertaking those EER measures [74]. In the reviewed works, it is found to be relevant for heat pumps [92], [101].

Often *economic motives* are correlated with decisions to renovate. For example, homeowners tend to renovate when they desire to save costs on energy bills [85], [91], [94]. This usually happens when households perceive their current energy bills as too high [93], [102] or expect the prices to rise in the future [90]. Homeowners who have *plans to move and sell* their dwellings in the next few years are significantly less likely to implement renovations [76],

[83], 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.* Subsidizing PV is effective, as it increases the adoption rate [84]. The probability of choosing alternative heating systems increases significantly for subsidy recipients [93]. In addition, receiving subsidies increased the chances of performing more than one EER [74]. On the other hand, Michelsen and Madlener (2012) report that subsidies did not show any significance for adopting heat pumps [92].

Studies show that we underestimate the effect of *social influence* and that our choices are influenced by our family, friends, neighbors, or other peers [72]. 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 [104]. In addition, the PV adoption is associated with the positive influence of neighbors, friends, and the community [91]. 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 [87].

In summary, the contradictory results of previous studies on determinants of EER adoption demonstrate that the context of each studied case is important for consideration. Furthermore, there are differences in the relationship between predictors of EER adoption observed within a country as well as across categories of predictors. Therefore, it is important to examine further the observed variables related to the EER adoption. We do so in the context of the Netherlands using the latest Dutch survey 2021 to obtain a clear understanding of factors that matter for the energy transition in this particular case.

3.3. Data and Methodology

The empirical analysis relies on principal component analysis and regression analysis. The combination of these methods is familiar as it has been known since the late 1950s [105]. 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. 3, first, actual variables from the Dutch household survey are selected based on the literature (Section 3.3.1). Second, principal components that capture the most variation in the dataset are obtained, as described in Section 3.3.2. Finally, based on the PCA scores matrix, logistic regression models for four EER decisions are performed (Section 3.3.3).

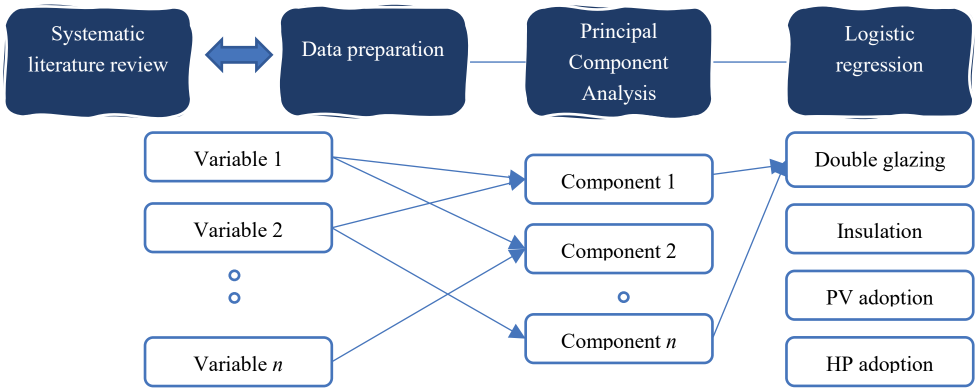

Figure 3. 3. Main steps of the empirical approach

3.3.1. 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 [80]. 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, we examine the characteristics of 25,659 homeowners[16] 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 (Figure A3. 1, Figure A3. 2 in the Appendices). The variables used in the regression analysis as dependent variables are listed in Table 3. 2.

Table 3. 1. Description of the input variables (N=25,659) [80]

Variable name	**Description**	**Variable type**	**Mean**	**SD**	**Median**	**Min**	**Max**
Length of residence	Number of years since a respondent bought a house	numerical	17.42	13.67	15	1	90
Building age	Number of years since respondent's house was constructed		51	45	44	0	1016
Income	Disposable income of household (source: CBS, 2020)		60,471	54,750	52,896	-212,024	1,306,182
House value	Property value as evaluated periodically by municipalities, in the legal		351,826	187,894	307,000	25,782	4,875,000

[16] A sample after removing tenants and missing information.

	framework of the law on property values (source: WOZ, 2021)						
Wealth	Household's wealth defined as total assets minus liabilities (i.e., loans)		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)		143	87	127	10	2,700
Electricity consumption	Annual electricity consumption (source: grid company)		3,201	1,561	2,931	0	11,249
Gas consumption	Annual gas consumption (source: grid company)		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)		2.23	0.76	2	1	3
Household size	Household size ('1-person' to '5 or more' people)		2.45	1.18	2	1	5
Urbanization level	Urbanization level of a neighborhood (based on the number of addresses in the surrounding, 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, negative to positive)	1.44	0.85	1	1	5
Contact with neighbors	"I have a lot of contact with immediate neighbors" ('totally disagree' to 'totally agree')		3.59	1.00	4	1	5
Home satisfaction	"Satisfied with current home"		4.51	0.62	5	1	5
Environment satisfaction	"Satisfied with the living environment"		4.30	0.75	4	1	5
Neighborhood engagement	"I live in a nice neighborhood where people help each other and do things together"		3.49	0.93	4	1	5

Neighborhood insecurity	"Afraid of being harassed or robbed in this neighborhood"		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		0.70	0.46	1	0	1
Past maintenance (indoor)	Past indoor maintenance, e.g., kitchen or bathroom renovation or new floor		0.49	0.50	0	0	1
Existing insulation	Existing insulation (roof, floor, walls) - beyond the past 5 years		0.71	0.45	1	0	1
Existing double glazing	Existing double glazing (or better, e.g., triple glazing) - beyond the past 5 years		0.71	0.45	1	0	1
Existing PV	Existing solar panels - beyond the past 5 years		0.09	0.29	0	0	1
Existing heat pumps	Existing heat pumps - beyond the past 5 years		0.02	0.14	0	0	1

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 [106], [107]. We argue that previously used variable "renewed boiler" [72], [76] is not a sustainable measure, as it concerns the renewal of a gas boiler.

3.3.2. 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 [108]. Mathematically, it derives from a *change of variable* in linear algebra where original matrix of predictors **X** is transformed into **Y**, both of dimension n x p (dataset with n observations, p variables), by multiplying with an unknown matrix **A** *(p* x *p):*

$$Y = XA$$

The principal components (PC) are the columns of the transformed **Y** and the linear form of the first principal component can be described as a linear combination of p original variables $x_1,\ x_2, .., x_p$:

$$y_1 \;=\; a_{11}x_1 \;+\; a_{12}x_2 \;+\; \dots + \; a_{1p}x_p = \sum_{i=1}^{p} a_{1i}x_i$$

y_1 is maximized given the constraint that the sum of the squared weights (for each PC across all variable) is equal to one[17]: $\sum_{i=1}^{p} a_{1i} = 1$. Although the number of calculated PCs can equal the number of variables, only a few are usually sufficient to capture most of the variation in a given dataset. The main outputs of PCA are the weights vector $a = (a_1, a_2, \dots, a_n)$ associated with each PC and its variance λ. In the data, we find these outputs from the original matrix **X** with $p = 25$ predictors of EER adoptions using the R package "psych" [109]. It is based on the eigenvalue decomposition method, which involves finding eigenvectors and eigenvalues from the covariance or correlation matrix.

To compute the PCA, first, we generate the mixed correlation matrix by calculating Pearson correlations for the continuous variables, polychoric correlations for ordinal (or polytomous) items, and tetrachoric correlations for the dichotomous items (see Figure A3. 3) [109]. Then, the eigenvalues and eigenvectors 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 is done via the "principal" function of the same package, where the number of PCs and the type of rotation[18] have to be supplied. The number of PCs are identified using Catell's scree plot test [110], which is the graphical representation of Kaiser's criterion [111]. Hence, components with eigenvalues higher than one (n=8) are retained. Orthogonal rotation varimax is used, reflecting that the output components are uncorrelated with each other [112].

The weight matrix **A** contains the component loadings, which indicates the weight of original variables when calculating each PC. The higher the loading is, the stronger the linear correlation is, while the sign indicates the direction of correlation. For the interpretation, we focus on components with loadings higher than 0.35 (Table 3. 3).

[17] It can also be scaled, e.g., the psych package's "principal" function uses a scaling factor, and the sum of squared weights is more than 1.

[18] Rotation is a pattern of loadings where each item loads strongly on only one of the factors (maximizing high item loadings), and much weaker on the other factors (minimizing low item loadings) [116]. Rotation serves to produce a more interpretable and simplified solution and can be orthogonal or oblique.

3.3.3. Regression models

Logistic regression is used to estimate the relationship between a binary dependent variable and a number of independent variables. Using PCA is a viable method to address a multicollinearity problem in regression models [108], [113]. 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. Principal component scores represent each component for each observation. They are calculated by multiplying the zero-mean design matrix with the matrix created from the eigenvectors of remaining PCs (i.e., where eigenvalues <1) sorted in a descending order [114], [115].

Logistic regression models are run to estimate the factors that are associated with the decision of homeowners to adopt each type of EER implemented in the last 5 years (2016-2021): (1) *windows insulation*, i.e., installing double-glazing; (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 having implemented a respective measure is calculated following the formula:

$$p = \frac{1}{1 + e^{-(\beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_k x_k)}}$$

where, p denotes the odds of the measure adoption (in the past 5 years), and x corresponds to the principal component scores. To measure the goodness of fit of the logistic regression models, we use McFadden pseudo R-squared[19] [117].

3.4. Results and Discussion

3.4.1. Descriptive statistics

As summarized in Figure 3. 4, out of 26,222 homeowners in the analyzed sample, 38% (N=9,981) has adopted at least one EER measure. Most of these adopters implemented one (67% 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. 4).

[19] 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 [117].

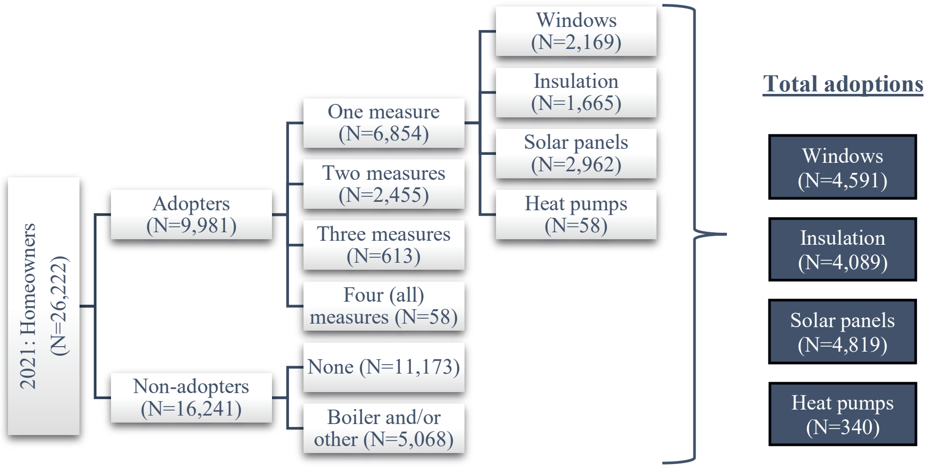

Figure 3. 4. Number of EER adopters and non-adopters; total measures adopted

Similar to previous findings from 2018 and 2012 [72], [94], the majority of renovators have undertaken these EER measures because they were necessary for maintenance, to lower the energy bill and to make their home more pleasant (Figure 3. 5). 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. 6). 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 state that "they haven't gotten around it yet", meaning that either they find this topic very complex or lack time and other resources to deal with this issue.

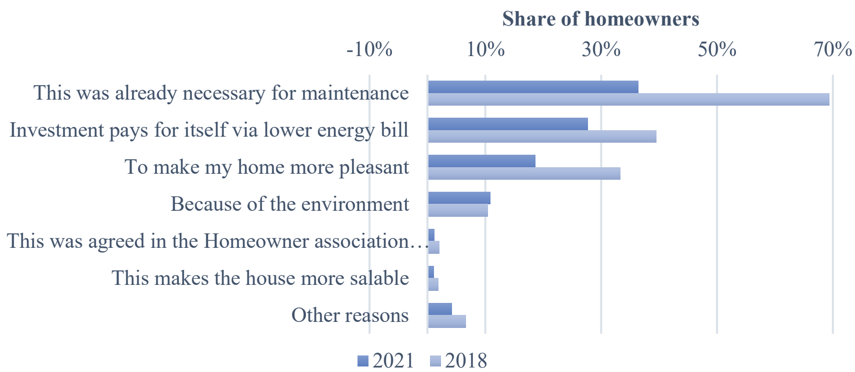

Figure 3. 5. Reasons for implementing EER (N2021=15,049, N2018=14,413)

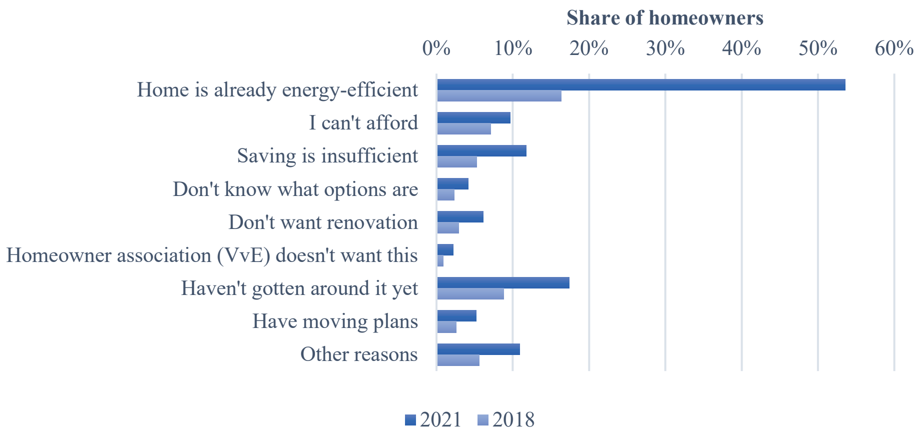

Figure 3. 6. Reasons for not implementing EER (N2021=11,049; N2018=26,588)

3.4.2. Characterizing principal components

The PCA combines 25 variables in eight components (Table 3. 3): (1) single-family houses in rural areas, (2) wealthier households with larger homes, (3) older, smaller households in long-owned homes, (4) newer houses with EER already in place, (5) homeowners satisfied with their homes, (6) homes with past maintenance, (7) homeowners actively engaged in their neighborhoods, (8) safer neighborhoods with highly educated inhabitants. 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.

Table 3. 3. Component loadings

Variables	Components 1	2	3	4	5	6	7	8
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 neighboors							0.85	
Want to move					-0.80			

Urbanization 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		

Single-family houses in rural areas

The first component refers to single-family houses in rural areas, showing that these types of homes are located in less urbanized 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 energy. The location correlates with the dwelling type, as single-family houses are predominant in the suburbs and rural areas of the Netherlands (Figure A3. 4). Moreover, such houses tend to be occupied by larger households with more people, e.g., families with children, which might lead to a correlation with the energy demand. Overall, this component illustrates that larger families living in larger single-family houses in rural areas have higher energy demands.

Wealthier households with larger homes

The second component shows a positive correlation between property value, income, wealth, and home area size, highlighting 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 (i.e., mostly single-family homes as shown in Figure A3. 8), despite larger houses having greater needs for electricity and gas (i.e., used for heating a larger living area and for powering larger numbers of electronics and devices). The correlation between these variables is consistent with the previous studies [100], [118], [119].

Older, smaller households in long-owned homes

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.

Newer houses with EER already in place

The fourth component depicts the relationship between building age, gas consumptions, existence of insulation, energy-efficient windows, and heat pumps. This dimension notes that homes in more recently constructed buildings tend to already have insulation[20], energy-efficient windows, and heat pumps. Figure 3. 7 demonstrates the proportion of households with existing insulation, which likely refers to the minimum U-value of 2.5 m^2K/W set by the Building Decree (Bouwbesluit) in 1992 [120]. 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.

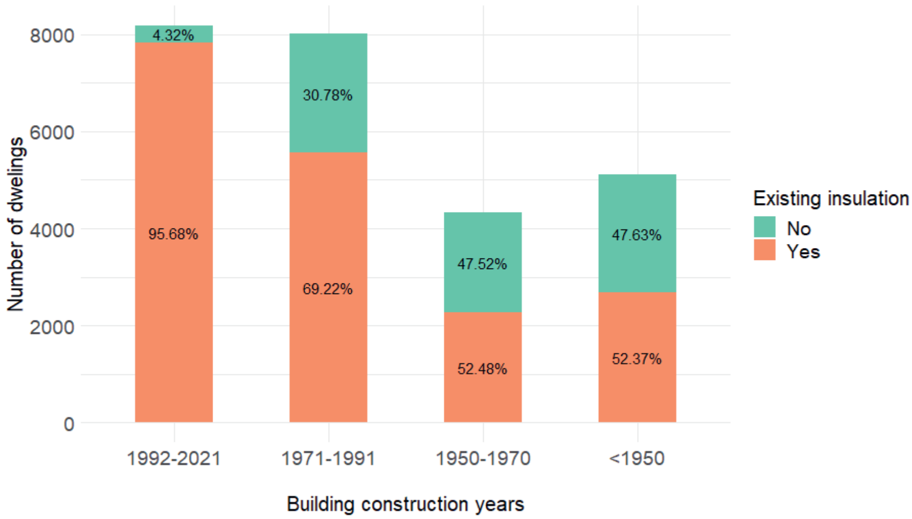

Figure 3. 7. Number of dwellings with previous insulation (before 2017) vs. construction year category

Homeowners satisfied with their homes

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. This component includes the three variables that have relatively strong loadings.

[20] The survey data do not reveal what level of insulation they have. However, every six years WoON survey includes an "Energy module" with more details on the specific characteristics of these EER measures, but only for a subset of a total survey sample [80].

Homes with past maintenance

The sixth component pertains to owner-occupied residences that have undergone both past outdoor and indoor maintenance[21]. This dimension emphasizes that households that have completed outdoor maintenance are also likely to have completed indoor maintenance. However, this component also implies that these households are less likely to have invested in heat pumps and solar panels.

Homeowners actively engaged in their neighborhoods

The seventh component refers to positive association between neighborhood cohesion which is characterized 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. This dimension thereby represents the cohesion among neighbors and satisfaction with the neighborhood.

Safer neighborhoods with highly educated inhabitants

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. As higher education and higher incomes are often correlated [121] and the sample illustrate this relation too (Figure A3. 9), this component could indicate wealthier neighborhoods.

Summary of the PCA results

In summary, the extracted eight components[22] explain 65% cumulative variance (Table 3. 4) with each component explaining about 5-10% of variability. In PCA practice, researchers often retain first few components that explain around 70% of total variance. In a similar study, Michelsen and Madlener (2013) obtained a cumulative variance of 61% [99].

Table 3. 4. The sum of squared weights (SSW) and variances explained by the PCA (n=8)

	Comp.1	Comp.2	Comp.3	Comp.4	Comp.5	Comp.6	Comp.7	Comp.8
SSW	2.56	2.48	2.38	2.01	1.93	1.86	1.73	1.22
Proportion Var	0.10	0.10	0.10	0.08	0.08	0.07	0.07	0.05
Cumulative Var	0.10	0.20	0.30	0.38	0.45	0.53	0.60	0.65
Proportion Explained	0.16	0.15	0.15	0.12	0.12	0.12	0.11	0.08
Cumulative Proportion	0.16	0.31	0.46	0.58	0.70	0.82	0.92	1.00

[21] Outdoor maintenance refers to such works as roof construction, exterior wall work or paint, or changing window frames. Indoor maintenance includes floor work, plastered walls or ceilings, kitchen or bathroom renovation.

[22] We consider the components with eigenvalues higher than one (see the scree plot in Figure A3. 7).

3.4.3. Regression results

To uncover the factors associated with EER investment decisions, Table 3. 5 presents results for windows insulation, roof, floor, and walls insulation, PV adoption, and HP adoption of homeowners across the Netherlands between 2016 and 2021. We discuss the results in terms of the importance of components for EER decisions (i.e., significant and high values indicate stronger likelihood).

Table 3. 5. Logistic regression results of having invested in EER over the past five years, N=25,659

	Windows	Roof, floor, walls	Solar panels	Heat pumps
1. Single-family houses in rural areas	0.123***	0.372***	0.514***	0.439***
	(-0.022)	(-0.027)	(-0.023)	(-0.075)
2. Wealthier households with larger homes	-0.432***	-0.448***	0.060***	0.313***
	(-0.023)	(-0.026)	(-0.016)	(-0.034)
3. Older, smaller households in long-owned homes	0.078***	0.019	-0.022	-0.317***
	(-0.021)	(-0.023)	(-0.017)	(-0.061)
4. Newer houses with EER already in place	-1.732***	-2.430***	0.055***	-0.114**
	(-0.03)	(-0.038)	(-0.02)	(-0.057)
5. Households satisfied with their homes	-0.043*	-0.117***	0.271***	0.726***
	(-0.022)	(-0.025)	(-0.02)	(-0.085)
6. Homes with past maintenance	1.725***	1.826***	0.428***	0.306***
	(-0.04)	(-0.045)	(-0.022)	(-0.063)
7. Households actively engaged in their neighborhoods	0.003	0.067***	0.053***	0.06
	(-0.019)	(-0.022)	(-0.017)	(-0.057)
8. Safer neighborhoods with highly educated inhabitants	-0.038*	0.095***	0.166***	0.197***
	(-0.02)	(-0.024)	(-0.018)	(-0.063)
Constant[23]	-2.276***	-2.878***	-1.615***	-4.741***
	(-0.027)	(-0.036)	(-0.018)	(-0.077)
McFadden's pseudo R-squared	0.242	0.366	0.053	0.072

Notes: *p<0.1; **p<0.05; ***p<0.01; standard error (SE) is reported in parentheses

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

The results of the model reveal a strong association between single-family homes located in rural areas and the adoption of all EER measures, with the strongest likelihood for solar panels. This is confirmed by many studies [70], [76], [84], [94], [97], [100], [103], [122] and

[23] A significant and low value of the constant suggests that the probability of the outcome occurring is relatively high when all predictor variables are at their maximum levels.

could be because single-family homeowners have the autonomy to make independent decisions on installing PV. Conversely, in multi-family homes, a majority consensus among residents is needed before a PV system can be installed as they share a common roof [123]. Furthermore, the model results indicate that these houses are more likely to adopt heat pumps (HP) as well as building envelope and windows insulation.

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 window insulation and insulation of 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 A3. 5). Moreover, living in larger houses require higher energy demands (as seen in Section 3.4.2), where energy efficiency might be essential.

The likelihood of EER adoption by older, smaller households 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 window insulation. This is in line with the findings of Nair et al. (2010) that homeowners living long in their houses with old windows are more likely to install the new ones [85]. On the other hand, the likelihood of these households investing in heat pumps is negative. Finally, the model does not indicate any correlation between these households and the adoption or non-adoption of solar panels and the insulation of roof, floor and walls.

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

The model results indicate that there is a significant negative correlation between households living in newer houses with EER already in place and the adoption of any type of insulation. This suggests that households living in newer homes with EER in place are less likely to invest in additional insulation. This predictor is straightforward, and it is also supported by the fact that many homeowners consider their homes already energy-efficient (Figure 3. 6), and therefore, they do not see the need to renovate. Similar to this finding, but not as strongly, owners of newer houses with existing EER are less likely to adopt HPs.

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 insulation of windows, as they have already implemented these measures in the past according to the survey responses (Figure A3. 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 insulating their windows as well as 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 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.

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 now show any correlation with the adoption or non-adoption of window insulation and the adoption of HPs.

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

The results reveal that homeowners who live in safer neighborhoods with highly educated residents have a higher likelihood of investing in solar panels and heat pumps. These households are also more likely to adopt the insulation of roof, floor, and walls, though, with a lower coefficient. Moreover, their active contact with the neighbors can influence the decision to insulate. However, in contrast to these three measures, households that are living in safer neighborhoods with highly educated residents are less likely to adopt the windows insulation.

3.4.4. Discussion, limitations and future research

This study 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 connection to installing solar panels or insulating their roof, floor, or walls. Homeowners often renovate in the early years of living in a new home as part of adapting a new place for a living [69], [101]. According to the data used in our study, necessity is a major motivator for Dutch homeowners to adopt. Additionally, savings on energy costs is another factor affecting the adoption decision. However, older homeowners living in long-owned dwellings may not have the motivation to invest, as they may not see the long-term financial rewards, or may be reluctant to switch to a new system that they are not familiar with.

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 [104] or PV [91]) and higher trust in the community [124], as such homeowners may be more likely to receive credible information and support from their neighbors. This highlights the potential for energy transition initiatives to be implemented bottom-up [125], [126], [127]. 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. As correlation does not mean causality, more in-depth qualitative research is necessary to find out the reasons for such observations.

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 organizational obstacles to do so. Unlike multi-family buildings, they do not share envelopes or roofs with neighbors, and can renovate with less hurdles [128], [129]. In addition, it is more challenging to install PV in older city centers, due to the irregular shapes of roofs [121]. The model results also show a strong link between rural single-family homes and HPs adoption as well as building envelope and windows insulation. 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 3.4.1, 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 [130].

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. On the other hand, they 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, therefore, future research is necessary. 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.

As the survey we used in this study 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. Also, 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. Thus, it is imperative to study how the decisions of households changed in 2022 and what we can learn from it.

3.5. 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 become inevitable. The purpose of this study was to determine factors associated with homeowners' decisions on energy investments and to outline possible policy improvements promoting the EER adoption among the Dutch homeowners. We examined four EER measures including window double-glazing, roof, walls, and floor insulation, and the adoption of solar panels and heat pumps. First, we conducted a systematic literature review to identify the potential predictors of EER adoption decisions. We subsequently used a principal component analysis to reduce their dimensionality (from 25 to 8 predictors) and conducted a logistic regression analysis to uncover further the relationship between the components and the EER adoption. The combination of these methods is valuable for deeper and more meaningful analyses and interpretation of the findings. Then, based on these analyses and key findings summarized in Section 3.4.4, we offer a list of recommendations that could be of use to the Dutch government and beyond for accelerating the energy transition:

1. Enabling the financial and technical know-how support for elderly to implement EER

While the 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 may not effectively reach this group of homeowners.

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

Safer and more cohesive neighborhoods being more likely to adopt the EER indicates a promising potential of 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. By promoting 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 a hard-to-reach group. Earlier studies have already confirmed 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 regard 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. Also, obligations to renovate the least performing buildings (which is currently under discussion in the EPBD recast as Minimum Energy Performance Standards) could be an effective measure in this regard.

4. Increasing awareness and making the information more accessible

The positive impact of neighborhood cohesion on EER adoption showcases that the information and awareness are important for increasing energy efficiency and adopting solar panels. Engagement with neighbors can play a crucial role in decision making for such investments, as community support and information from the neighborhood can positively influence the EER adoption. Governments should therefore create awareness programs and make information easily accessible. This is also relevant for homeowners looking to perform renovations. Earlier studies indicate that homeowners who have undergone renovations become more informed about the cost-benefit of retrofits, and are more motivated to enhance their home's energy efficiency, comfort, and resale value [131]. However, a common barrier for these homeowners is their limited knowledge of reputable companies, and trust on them in executing renovations [131]. Thus, increasing awareness and making the information about EER adoption more accessible will significantly contribute to energy efficiency.

5. Requiring all homeowners to obtain an energy efficiency label

Our study 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. The Dutch standard for newly-constructed dwellings (built after 1992) is relatively effective as most of them are insulated to some extent and have a certain share of EER in place. To determine the current energy efficiency of these houses, as energy efficiency standards are evolving, an energy efficiency label for all homeowners might be necessary. It is crucial to include all homeowners, including old homeowners and those who inherit houses, in the energy efficiency labeling initiative. Moreover, introducing the minimum level of retrofitting (similar to office buildings in the Netherlands) and punitive measures for not conforming could be very effective, as people tend to adopt EER mostly when necessary.

In conclusion, this study identifies population groups that are still lagging behind in energy transition in the Netherlands. Therefore, these policy implications can be a useful addition to the current policy schemes of the Dutch government as they ensure inclusive and just energy transition for everybody.

Appendices

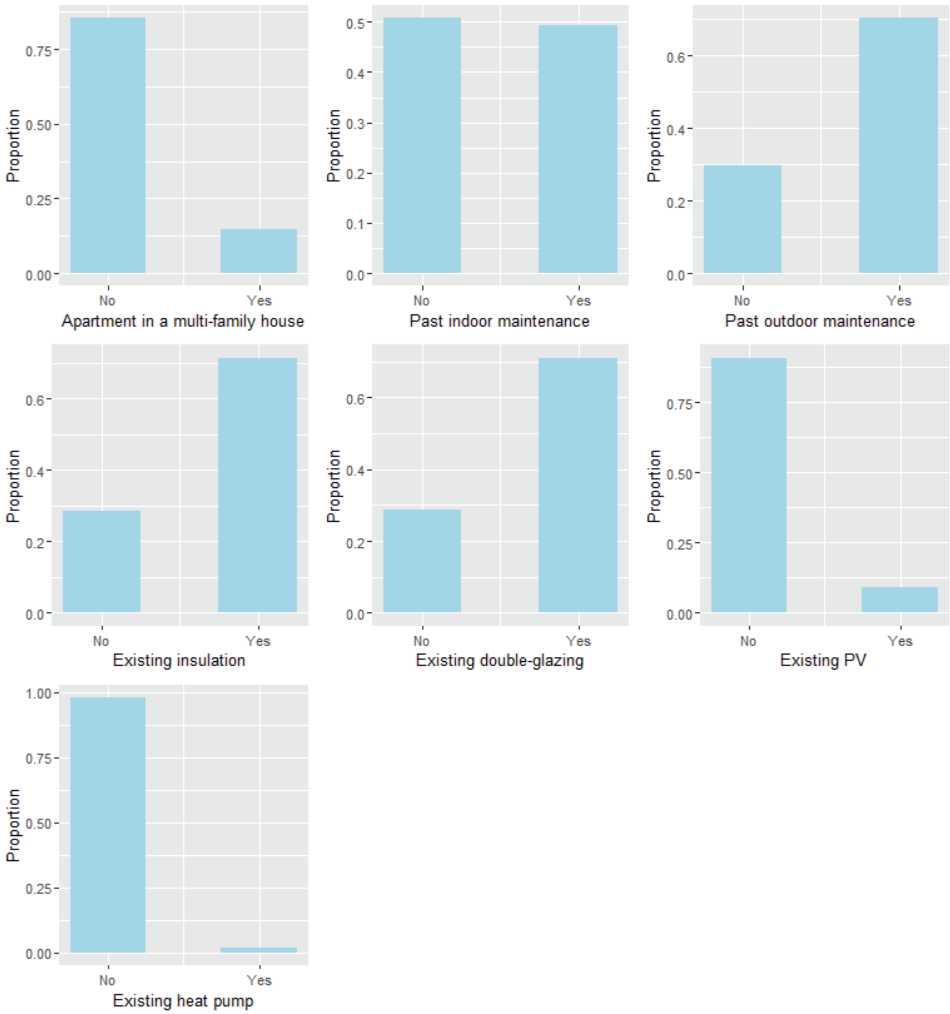

Figure A3. 1. Frequency histograms for binary variables

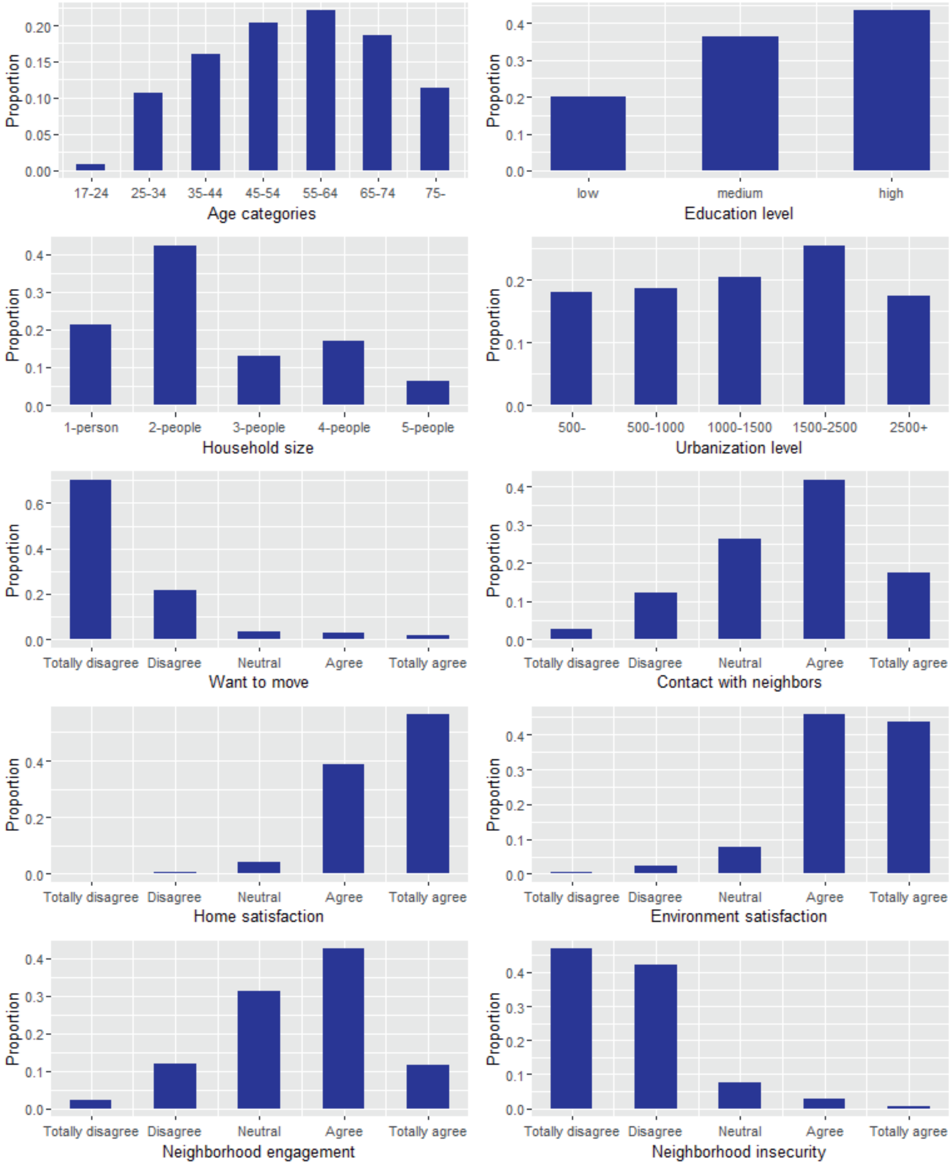

Figure A3. 2. Frequency histograms of the ordinal variables

Chapter 3

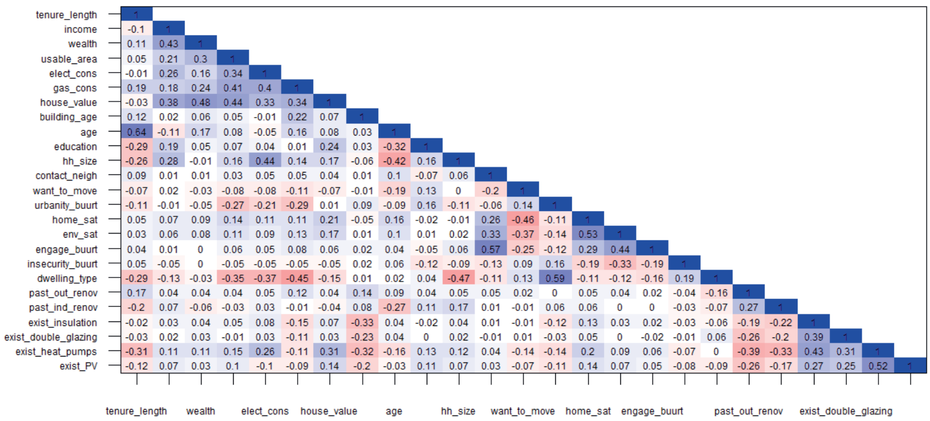

Figure A3. 3. The mixed correlation matrix

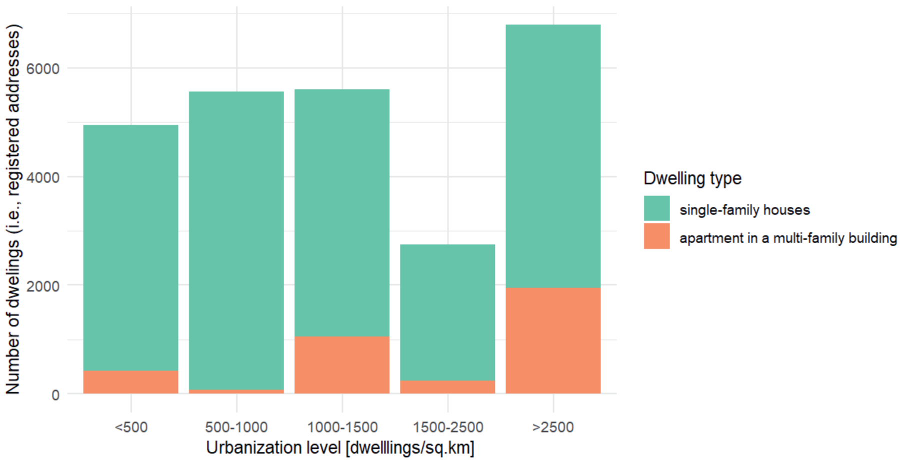

Figure A3. 4. Dwelling types by urbanization level

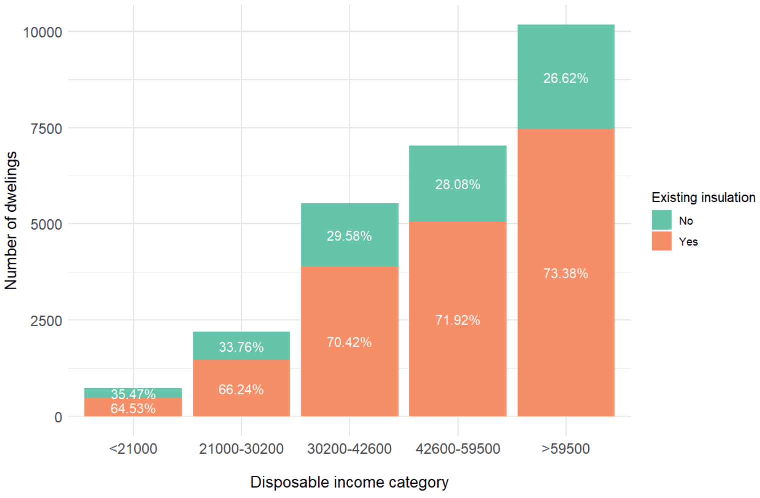

Figure A3. 5. The relationship between existing insulation and household's disposable income

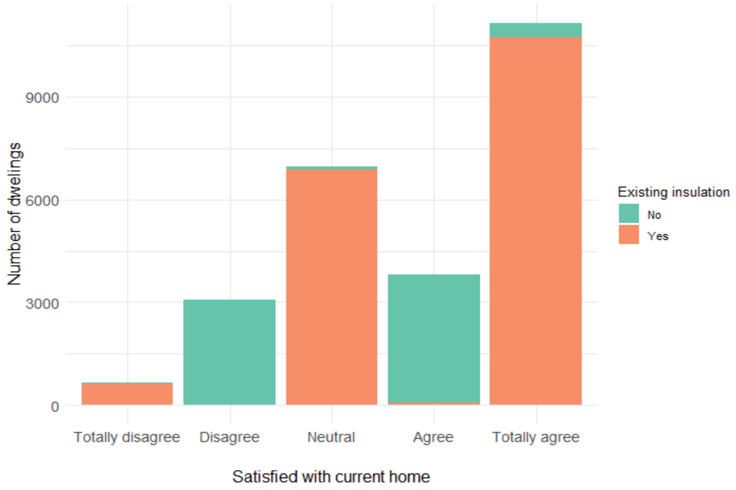

Figure A3. 6. The relationship between existing insulation and homeowner's satisfaction with home

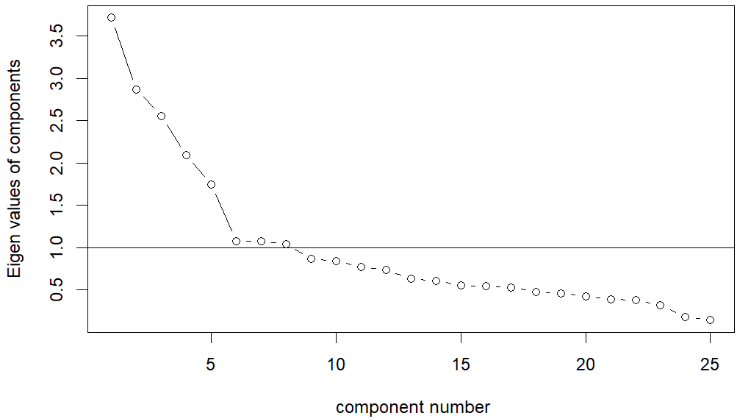

Figure A3. 7. The scree plot

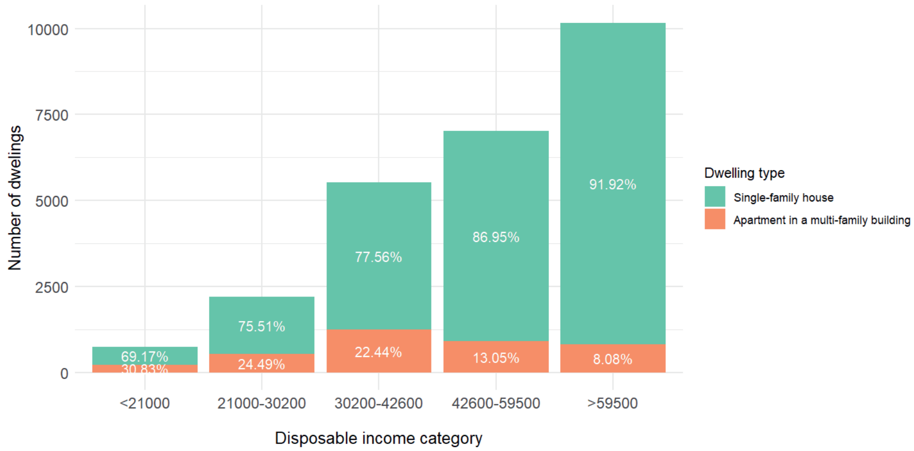

Figure A3. 8. The relationship between dwelling type and disposable income

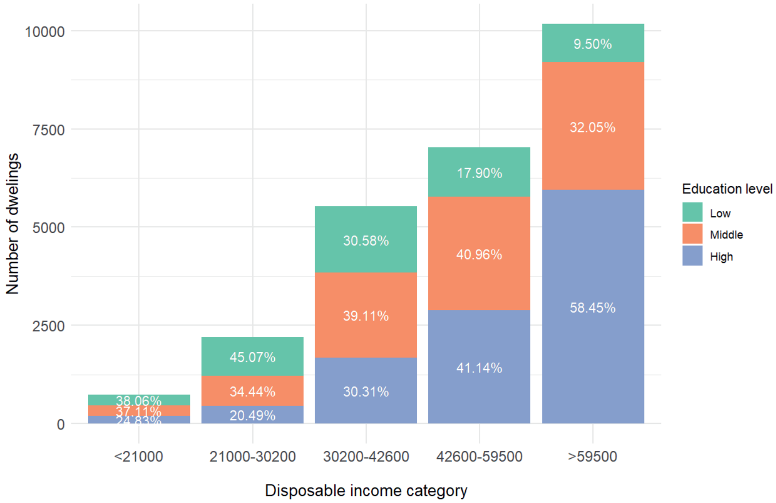

Figure A3. 9. The relationship between disposable income and education

4

Chapter 4

ENERGY Pro: spatially explicit agent-based model on achieving Positive Energy Districts

This chapter is based on: E. Derkenbaeva, G.J. Hofstede, E. van Leeuwen, S. Halleck Vega, J. Wolfers, “ENERGY Pro: spatially explicit agent-based model on achieving Positive Energy Districts,” 2023.

Abstract

This article describes the *ENERGY Pro* agent-based model using the Overview, Design Concept, and Details + Human Decision-making (ODD+D) protocol. The model is empirically explicit and aims to investigate the adoption decisions of homeowners in Amsterdam on different energy-efficient retrofitting (EER) measures. Following the ODD+D protocol, this study uncovers the conceptual framework used for model construction, the spatial microsimulation process of expanding the data, and the model implementation details. The article also describes sensitivity analysis, validation results, and how to use and adapt the model. With this article, the authors aim to make the model replicable and accessible to other researchers and inspire them using the combination of social simulation and spatial microsimulation in studying the energy transition.

4.1. Method details

In light of the current crises, increasing CO_2 emissions, climate change, and energy crisis have become environmental commons dilemmas. The commons dilemmas arise when individuals share a common (environmental) resource, e.g., the atmosphere, and their use of that resource negatively affects the welfare of others [132], [133]. As energy transition is part of the solution for these dilemmas, sustainable energy behaviors are germane. Sustainable energy behaviors include adopting renewable resources, implementing energy efficiency measures in buildings, and using more sustainable and energy-efficient appliances [134]. The *ENERGY Pro* model aims to investigate such behaviors of households in Amsterdam to understand to what extent households can contribute to tackling these environmental commons dilemmas through achieving Positive Energy Districts (PEDs). PEDs are energy-efficient, self-sufficient, and carbon-neutral urban areas and are considered one of the possible pathways toward urban energy transition [1], [135].

Among different simulation approaches, agent-based modeling (ABM) is the key approach to quantitatively studying the behaviors of heterogeneous agents and their interactions over time [125]. Designed for bottom-up analysis, the ABM help capture individuals' emergent behavior and explain more complex macro behavior observed in the real world. The predominant advantage of using the ABM in researching the energy transition is its ability to account for complexity [136]. An energy system is a complex adaptive system comprised of heterogeneous agents and technologies [135]. There are substantive ABM energy transition-related applications, but examples of spatially-explicit empirically-driven energy models are still scarce [137].

This simulation model aims to explore how energy consumers become *ENERGY Pro*sumers by adopting different energy-efficient retrofitting (EER) measures. The model is empirically explicit and includes two layers – spatial and social. The spatial layer represents residential buildings in Amsterdam and is informed by the BAG[24] (Basisregistratie Adressen en Gebouwen) data [138]. The social layer denotes Amsterdam households informed by the WoON (WoonOnderzoek Nederland) Dutch survey 2021 [139] and Census data [140]. The model is developed in NetLogo 6.3.0. Additionally, the model heavily relies on R programming language to perform more complex operations, such as spatial microsimulation and other time-expensive operations.

This article describes the *ENERGY Pro* model using the ODD+D protocol (Overview, Design Concept, and Details + Human Decision-making) following the format of Grimm et al. (2006) [141] and Müller et al. (2013) [142]. The ODD+D protocol is a standardized approach to describe agent-based models, which consists of three main sections: (1) Overview, (2) Design concepts, and (3) Details. The protocol is widely accepted and used as it offers easy-

[24] Dutch automated system of Basic Registration Addresses and Buildings

to-read documentation of models and facilitates their replication [143], [144]. Following the section on ODD+D protocol (Section 4.2), this study also offers sensitivity analysis (Section 4.3) and presents model calibration and validation (Section 4.4). The last section describes how to use and adapt the model (Section 4.5).

4.2. ODD+D protocol

4.2.1. Overview

Purpose

The purpose of developing the *ENERGY Pro* model is to explore households' decision-making on adopting EER with a particular focus on double glazing, insulation of walls, roofs, and floors, and the adoption of residential solar photovoltaic (PV) and heat pumps. Using the input survey to mimic the Dutch households, this model aims to understand households' contribution to urban energy transition in Amsterdam by 2030. A key motivation in developing this model is to allow for simulations of possible policy interventions to inform policymakers on observed energy-related decision-making patterns of homeowners and factors affecting these patterns.

Entities, state variables, and scales

The *ENERGY Pro* model includes two entity types – households and EER measures. The household subtypes considered in this study are homeowners and tenants. Though homeowners are the ones that make decisions on adopting EER, tenants are taken into account as they also consume energy and contribute to carbon emissions. State variables of the households and their description are presented in Table 4. 1. Households are defined by their socio-demographic and dwelling characteristics. Some of the survey data was recoded to fit the model's construct. While some variables are used to build the model, others are used for descriptive analysis only, enabling us to differentiate household types. The model is built with a rough assumption that all houses are suitable for adopting the measures.

EER measures include building retrofit measures (i.e., double glazing, insulation of roof, walls, floor, and heat pumps) and residential solar photovoltaic. It should be noted that storage batteries (considered an integral part of adopting either PV system or heat pumps, or both) are not common in the Netherlands and accordingly, are not included in this study. The state variables of these measures are presented in Table 4. 2. Each measure available to households is defined by its price. Each type of technology has a different monetary value, which changes over time. Some measures also have after-lifetime emissions, energy generation, electricity demand, and saved heat. EER technologies are not completely renewable and have minor after-lifetime emissions that should be considered. Electricity generation by PV depends on weather conditions already included in the calculation. Heat pumps have electricity demand to produce heat, while insulation measures save up heat use in houses.

Table 4. 1. State variables of households based on WoON 2021

Variable name	Description	Change
Socio-demographic characteristics		
Age	7 age categories: 18-22, 23-26, 27-34, 35-44, 45-54, 55-64, 65+	Dynamic
Ownership	Ownership status of an occupant: owner or tenant	Static
Education	3 categories of highest attained education: low, middle, and high	Static
Household composition	5 categories of household composition: single-person house, couple without children, couple with children, single-parent family, and other	Static
Household size	3 categories of household size: single-person household, two-people household, and three(or more)-people household	Static
Income	Annual disposable household income, continuous variable	Static
Income-cat	5 income categories: less than 21,000, 21,000-30,200, 30,200-42,600, 42,600-59,500, more than 59,500	Static
Wealth	Prosperity indicator that combines income, savings, and debts, continuous variable	Static
Social identity (cohesion)	Indicator of social quality – cohesion ranging between 0 and 1	Static
Contact with neighbors	A household has contact with immediate neighbors – range between 0-1 based on the Likert scale with an increment of 0.25, where 0 – totally disagree and 1 – totally agree	Static
Level of life satisfaction	Level of life satisfaction ranging between 0 and 1	Static
House landlord	6 categories of owners of rented houses: housing corporation, municipality, pension fund (or insurance company, investors or broker), private person, family, and other	Static
Dwelling characteristics		
Location	Neighborhood (Dutch: wijk) and district where a house is located	Static
Construction year	6 categories: built before 1946, 1946-1980, 1981-1990, 1991-2000, 2001-2010, built after 2010	Static
Dwelling type	2 categories of dwelling type: apartment and non-apartment	Static
Electricity consumption	Annual consumption of electricity in kWh	Dynamic
Gas/heat consumption	Annual consumption of gas/heat in m^3	Dynamic
Existing insulation	There is insulation (either of roof, walls, floor, or all) in the house, 1 – yes, 0 – no	Dynamic
Existing double glazing	There is double (or triple) glazing in the house, 1 – yes, 0 – no	Dynamic
Existing PV	There is PV in the house or building, 1 – yes, 0 – no	Dynamic
Existing heat pumps	There is a heat pump in the house, 1 – yes, 0 – no	Dynamic
Want to move	Household wants to move in the next 2 years, range between 0-1 based on the Likert scale with an increment of 0.25, where 0 – definitely not and 1 – found another home	Dynamic

Table 4. 2. State variables of EER measures

Variable name	Description	Change
Type of a measure	Double glazing, insulation, PV, heat pumps	Static
Product price	The monetary value of a product in euros	Dynamic
Price change	Change in product price every year in %	Dynamic
After-lifetime emissions	Some products have minor after-lifetime emissions, tons	Static
Energy generation	Average annual electricity generation by PV is calculated depending on weather conditions in kWh, and average annual heat generation by heat pumps in m^3	Static
Electricity demand	The electricity demand of heat pumps to produce heat in kWh	Static
Saved heat	Share of heat saved through adopted double glazing and major insulation in m^3	Dynamic

The *ENERGY Pro* model is spatially explicit. The model's spatial layer includes seven Amsterdam districts with a spatial resolution of individual residential buildings. Each cell or patch in NetLogo represents several buildings; each building and its households have individual characteristics (see Table 4. 1). However, these characteristics are aggregated per cell when the distribution of households or adopted EER measures is loaded (the color gradient is used for visualization purposes). The number of households allocated per cell differs depending on a scale represented on the interface, namely district or city. When only considering cells containing households, there are around 205 households per cell at the city scale. In contrast, at the district scale, there are, on average, 23 households per occupied cell (the example of Zuidoost district)[25]. Therefore, in order to have a higher resolution of the households and obtain more precise information, we focus on one district at a time.

The temporal resolution of the model corresponds to one year (one time step) covering a period of 10 years (2021-2030). The Dutch government aims to reduce carbon emissions by 55% compared to 1990 levels before 2030 [4]; therefore, 2030 is an important target for transforming energy systems, especially in urban areas that face many challenges. This simulation period is chosen to examine how much households in Amsterdam can contribute to this Climate Agreement goal. A one-year step is chosen because the annual energy balance is the most accepted one for calculating the energy balance of PEDs [135]. Also, EER adoption is a major decision that requires substantial time and investments, therefore, a one-year step works best for modeling this decision. Though a one-year step might limit exploring

[25] In this model, there are 10,000 cells (100*100) in total, 6,379 of which are within the borders of the Zuidoost district and 1 846 cells occupied by households. The total population of Zuidoost is 41,652 households (as such, 41,652 / 1,846 cells = 23 households per cell). Considering this district's surface area is about 22 km^2, each cell will represent 0.003 km^2 or 3,000 m^2 (i.e., 22 km^2 / 6,379 m^2).

the emergent behavior of the model, it is a common practice in building models of more complex systems such as the energy system [145].

The main global variables in the model include average households' annual carbon emissions in Amsterdam and electricity and gas prices changing yearly, and energy price uncertainty, among others. Energy prices change annually based on possible energy market fluctuations, while households' carbon emissions change according to the decisions of households on the level of energy consumption and adoption of the measures. More information on global variables is offered in Table A4. 1 in Appendix.

Process overview and scheduling

At the initialization stage, a setup procedure is executed. First, the spatial layer is set by clearing the entire NetLogo environment and loading the GIS dataset. The GIS procedure resizes the environment based on the coordinate system, allocates buildings to cells, assigns district borders, labels to districts, codes and names to neighborhoods, and buildings' construction year to cells. Second, the social layer with local and global variables is set by creating a population, assigning the values from the datasets to them, and allocating the households on the map. The setup procedure also creates the legend and, if enabled, a new random seed for reproducibility. Then, the list of similar neighbors is created, and energy generation and emissions are calculated.

After the initialization, the *ENERGY Pro* model performs the actions depicted in Figure 4. 1 each time step. One time step in this model is one year. In sub-step (1), the model checks the number of time steps left. The model stops running when the maximum time steps (i.e., 10) are reached. In sub-steps (2), (3), (4), and (5), the characteristics of the environment are updated. These characteristics include the EER measures' attributes (e.g., price), carbon emissions, energy generated by households, and energy prices. The environment update is followed by the steps of households. In sub-step (6), households interact with their similar neighbors, after which they evaluate their needs (7) and check if their behavioral control is positive or negative (8). If their behavioral control is positive (meaning they can satisfy their needs), they update their memory (9), and in sub-step (10), they can choose one of the reasoned decisions. If the behavioral control is negative, they skip updating their memory and are left with either automated decision strategies in sub-step (10). In sub-step (11), households evaluate the level of their need satisfaction. Collective decisions on PV adoption in multi-apartment buildings are made in sub-step (12) if activated in the simulation.

Through sub-steps (13), (14), and (15), there are more environment updates. The overview investments procedure updates the investment value of either of the four EER measures adopted by households (13). This procedure is followed by updating the investment score (14). Investment score update is run on a cell basis and assesses how many households living on a cell adopted any measure. They receive a score of 1 for each adopted measure (max. 4).

The scores of households living in one cell are aggregated within the interface for visual purposes. In sub-step (15), the characteristics of households that did not participate in a current time step (i.e., did not make decisions) are reset to their default values from the previous time step. These households will start making decisions in the next time step. Important to note that those households that participated in a current time step and are set to skip the following one are not affected by this procedure.

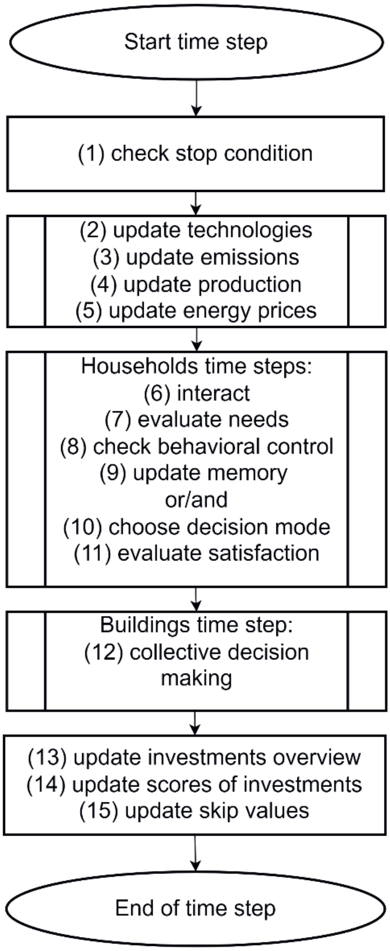

Figure 4. 1. Flowchart of the model's time step

4.2.2. Design concepts

The terminology and order of concepts are considered following Grimm et al. (2006) [141] and Müller et al. (2013) [142][26].

Theoretical and empirical background

The *ENERGY Pro* model's design is based on a theoretical framework *Consumat* that was developed by Jager et al. (2000) based on multiple behavioral theories on cognitive processes and underlying driving factors for behavioral change [146]. Energy-related decisions in this model are whether to invest in double glazing, insulation of roof, walls, and floor, and adoption of residential solar panels and heat pumps. The main decision-makers in the model are homeowners. Owners in the Netherlands have the right to make individual decisions on adopting the measures if they live in a single-family house that is a non-apartment dwelling (e.g., detached, semi-detached, terraced, etc.). However, they can only collectively decide about PV adoption if they live in a multi-apartment building sharing a common roof with other residents [147]. According to the statistics, apartment dwellings account for about 85% of the housing stock in Amsterdam [148], which means most of the PV adoption decisions will be made collectively. Therefore, we differentiate homeowners' individual and collective decisions in this model.

Tenants were also among the adopters based on the WoON Dutch survey 2021 [139], which can be explained by the fact that they might have received the permission of their landlords to adopt the measures. According to Dutch Civil Law [149], they do not have the right to adopt any measure without their landlord's consent. We include the variable on types of landlords of rented houses in the descriptive analysis to observe who is behind the decision-making. We also introduce a scenario with tenants making adoption decisions in order to evaluate their contribution to the energy transition goal.

Following the Consumat meta-model, households choose one decision strategy out of four: imitate, optimize, repeat, or inquire. The choice of a strategy depends on their *satisfaction* and *uncertainty* (Figure 4. 2). Satisfaction and uncertainty are, in reality, subject to social influences that can differ a lot between types of homeowners and types of built areas. If the satisfaction of *consumats* (i.e., agents in Consumat) is high, the consumats will choose one of the automated behavioral strategies and either repeat their previous actions or imitate similar consumats. While the satisfaction of consumats is low, the consumats will choose one of the reasoned behavioral strategies – to optimize their actions by finding a better solution to satisfy their needs or to inquire actions of other consumats (with strong and weak ties) that seem to be satisfying the needs. Uncertainty, in its turn, guides which of those two strategies of automated and reasoned behaviors consumats pursue. Each consumat has a particular level of uncertainty about their decisions and the future in general, as well as

[26] The concepts "Individual sensing", "Individual prediction", and "Submodels" are not applicable in this study.

uncertainty tolerance that determines to what extent a consumat is risk-seeking. More information on the conceptual framework is uncovered in the *Details* section.

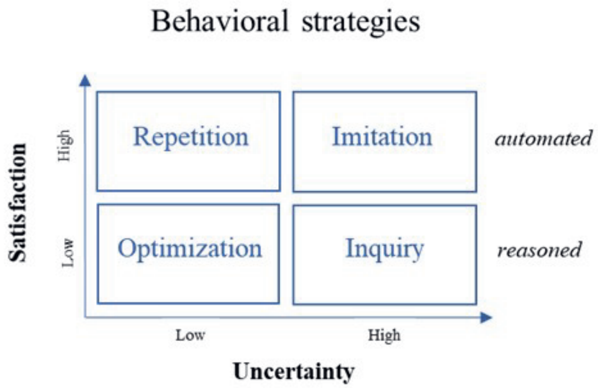

Figure 4. 2. Behavioral strategies based on Consumat [146]

The *ENERGY Pro* model is mainly based on empirical data from the WoON Dutch survey 2021 [139]. The data is available at a household level. The number of households from Amsterdam that participated in the WoON survey in 2021 is limited to 1,630, which is insufficient to analyze the city thoroughly. To use the real (even though limited) data and shed new light on available information, we use a spatial microsimulation approach that helps create approximations of individual-level data at high spatial resolution: households allocated to places [150]. A key step in spatial microsimulation is population synthesis, which combines the real individual-level data (with little or no geographical information) from the WoON survey and geographically-aggregated data (Census data). As a result of population synthesis in Amsterdam, we created a usable dataset with 447,685[27] households assigned to a neighborhood based on their characteristics. It is a little smaller than the actual number of households as several neighborhoods have been removed from the synthetic population dataset (see more specifics in the *Details* section).

Individual Decision-Making

At each time step, households update their socio-demographic and dwelling characteristics. Before households' decision-making process starts, they interact with other agents in their social network that are similar. Similar households are chosen based on several aspects discussed in the *Details* section. After interacting with similar agents, households evaluate their needs. Based on the original Consumat framework, there are three categories of needs – existence, social need, and personality [146]. Existence refers to having means for life, such as housing, food, and clothing. Social refers to the agent's place within its network(s),

[27] There were 476,008 households in Amsterdam based on Census data in 2021.

while personality reflects the agent's style and taste (different from others). Within each category, there can be several needs.

This study focuses only on two need categories – existence and social need. We consider the personality need to already be part of the social need as individuals are embedded within social networks, and their preferences are shaped by their interaction with others in their social environment [151]. As such, in the *ENERGY Pro* model, households' need for existence is their energy need, while their social need is their identity (i.e., belonging to a group, having social status) that can be satisfied if more similar neighbors adopt the same product. More information on constructs of need satisfaction and its calculation are offered in the *Details* section.

To satisfy their needs, households check their behavioral control. Behavioral control is the difference between households' abilities to consume available opportunities and the resource demand of available opportunities. Opportunities are the products and services (commodities) that an agent can use and have a certain capacity to satisfy the agent's needs (e.g., EER). In this study, abilities include legal rights to adopt EER measures, and availability of financial resources, while resource demand includes the availability of EER measures and their prices. More information on behavioral control is in the *Details* section.

Spatial aspects such as house location and proximity between buildings/households impact the energy-related behavior and decisions of households based on technical and social factors [152]. First, house location implies spatial characteristics (location in a particular part of the city) that play a role in decision-making based on technical features such as historical centers or newly built areas imposing possible constraints or creating opportunities. Second, proximity between buildings influences decision-making based on social factors allowing the interaction of (similar) neighbors. Temporal aspects also play a role in the decisions process of households. Technology becomes less expensive and more affordable over time, making it accessible to a wider population. Also, the population becomes more experienced and knowledgeable in adopting EER, which will be diffused in the social network through agents' interaction.

Learning/memory

Based on Consumat, memory is a learning tool of agents. Agents learn over time based on their experience and connection to their reference group (i.e., neighbors)[28]. In its memory, the agent keeps track of its adopted measures and knowledge of the agents in its social network. As such, every adopted measure by households or their similar neighbors provides a household with new information and experience. Agents update their memory only in reasoned mode, therefore, when they make their decisions on a behavioral strategy, they

[28] In this study, neighbors are chosen as a reference group based on previous studies' findings that proved the importance of the neighborhood and neighbors' impact on EER adoption [104].

choose between optimization and inquiry. More information on memory is offered in the *Details* section.

Interaction

In the *ENERGY Pro* model, households interact and create their reference group with others with similar location (neighborhood), age, and income. As such, the households create their social network with their similar neighbors. Each household has a set of similar neighbors and chooses one of them at each time step. However, the chosen neighbor does not necessarily reciprocate (i.e., does not choose back the same household). Similar neighbors might affect households' decisions on energy consumption behavior and adopting measures if they are satisfied and certain. After interacting and gathering information about their similar neighbors' experiences, households choose to either imitate their behavior and reduce energy consumption (by max. 25%) or inquire and adopt one of the EER measures adopted by their neighbors that they still have not adopted.

Households also interact with EER measures by adopting them. This interaction enables households to increase energy efficiency in the house and reduce energy consumption. On the contrary, if these measures are not adopted, households negatively affect the environment by contributing to carbon emissions caused by consuming non-renewable energy and living in an energy-inefficient dwelling. The emissions lead to and are not limited by environmental degradation, health issues, and climate change [153], [154].

The interaction of the environment with households also exists. Environment variables (i.e., macro-level variables) such as electricity and gas prices affect households' decision-making on energy consumption and adoption of measures. If energy prices change over time, households make consumption and adoption decisions accordingly. For example, if energy prices increase, households are more likely to reduce their energy consumption as it becomes less affordable and to try investing in EER expecting financial returns on investments.

Collectives

Based on the nature of the residential built environment, some collectives in the model, such as multi-apartment buildings, have to make decisions jointly. This applies to the decision to adopt solar panels because such buildings share a common roof. The majority of apartment owners' association (VvE) members must agree on this decision (often, a two-thirds majority is sufficient) before it can be implemented [147], [155].

Heterogeneity

The households in the model are heterogeneous. They differ in terms of their socio-demographic and dwelling characteristics. The survey data for developing this empirical model are based on a stratified sampling method to represent Amsterdam's population groups. Therefore, exchanging one homeowner with another would affect the simulation. In their decision-making, the homeowners generally differ in their satisfaction and uncertainty and, therefore, their chosen behavioral strategies.

Stochasticity

Households perform actions ordered by the modeler consecutively in random order. This applies to actions related to households' decisions, interaction with their similar neighbors (they randomly choose a different similar neighbor every time step from the list created during the setup procedure), decisions' implementation, etc. This is the standard mechanism of NetLogo.

Observation

As this study examines the EER adoption decisions of homeowners in Amsterdam, the graphical model output can demonstrate the provisional average adoption rate of all EER measures between 2021-2030 for all the city districts. Figure 4. 3 presents an example of the uptake of EER measures in Zuidoost over the simulation period. Based on the run shown in Figure 4. 3, the average EER adoption rate is higher in the southwestern neighborhood of "Gein" of Zuidoost. Yellow cells mean that the households that occupy them adopted between two and three different types of EER on average. In contrast, red cells spread across the district show that those households occupying the cells did not adopt any measures. We generally observe more orange and brown cells showing that the average number of adopted EER types varies between one and two. There is a limited number of cells that adopted between three and four EER types colored light green.

Figure 4. 3. Energy Pro model interface (example of Zuidoost)

The model's interface also includes plots on Consumat-related parameters (Figure 4. 4). The upper two plots on players' strategies show the four decision strategies households choose every time step. The middle two plots demonstrate the homeowners' level of need satisfaction (LNS) and uncertainty based on which they decide on a strategy. We observe that in Zuidoost, homeowners mostly optimize at the beginning of the simulation because of their low LNS and uncertainty, especially during the first time steps. The largest number of homeowners optimizing was in time step 1 (the year 2022). In the next time steps, the number of homeowners optimizing has been decreasing due to the larger number of homeowners with a higher LNS, but also growing uncertainty. The smallest number of homeowners chose imitating due to their higher LNS and higher uncertainty. We also observe sharp kinks in these plots as the data collected per time step, and the model has a coarse time granularity. The last two plots in Figure 4. 4 show the cumulative number of EER measures adopted over time. When the option of including tenants in decision-making is switched on, the model calculates their EER uptake. Under the baseline scenario, when only homeowners make adoption decisions, we can observe that in Zuidoost, the most adopted measures are double glazing and insulation, while the least is PV. We can also observe a rapid uptake of heat pumps.

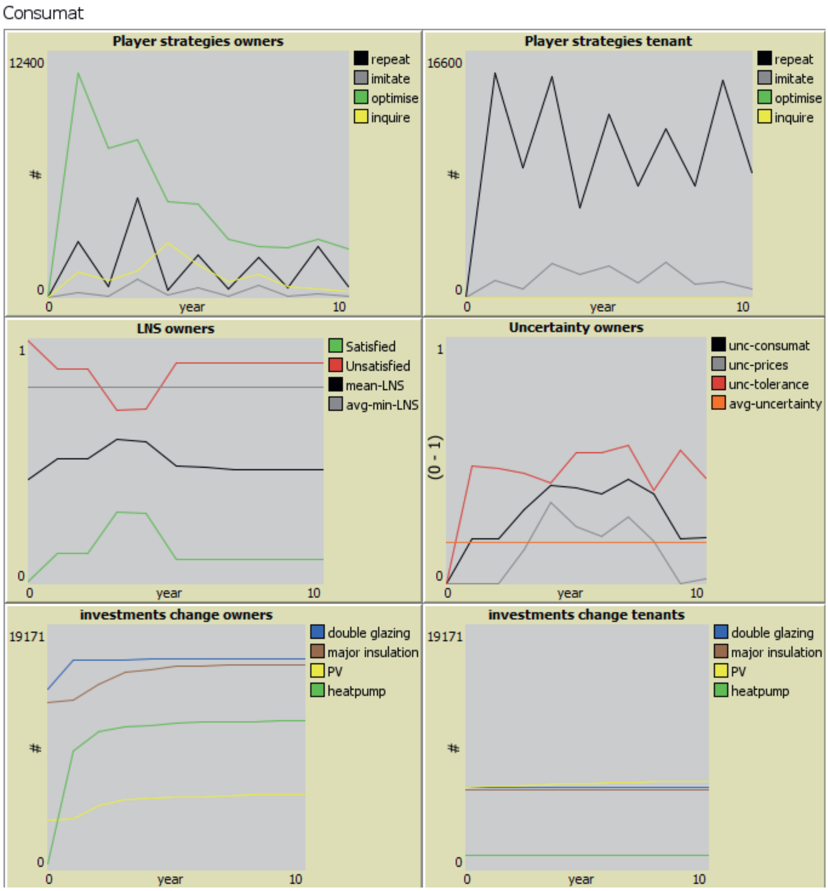

Figure 4. 4. Consumat-related parameters (example of Zuidoost)

4.2.3. Details

In addition to this section's standard subsections based on the ODD+D protocol, we also elaborate on the Consumat framework, synthetic population, and data imputation.

Implementation Details

The model is developed in NetLogo 6.3.0. At initialization, the model reads data from three files. First, BAG data includes information on local registered addresses and buildings, including their construction year. Second, the synthetic population dataset is based on WoON Dutch survey 2021 and Census data. While the BAG dataset is used for setting up the spatial layer, the synthetic population is used for setting up the social layer. Both the BAG data and the WoON data can be accessed by researchers upon request from their sources. Finally, the third dataset contains characteristics of EER measures based on openly available data on the internet.

Consumat

The basis of each Consumat behavioral strategy is determined by the level of satisfaction and uncertainty of decision-makers, which are in turn influenced by their individual characteristics. A decision-maker chooses the *Repetition* when their level of satisfaction exceeds the accepted minimal level and their uncertainty level is below their threshold of uncertainty tolerance. This indicates that the decision-maker is highly satisfied and certain, and there is no need to change their behavior. Repetition of satisfactory behavior is a central mechanism behind the development of habitual behavior [156].

When a decision-maker's level of satisfaction exceeds the accepted minimal level, but their uncertainty level is higher than their threshold of uncertainty tolerance, they will choose the *Imitation* strategy. In this scenario, the decision-maker is still satisfied but highly uncertain, which leads them to consider behaviors performed by peers whom they trust and care about (strong links) and imitate them. This behavioral strategy is driven by the social need to be part of a particular society or group, and successful behaviors performed by peers are likely to influence decision-makers to copy them when they are uncertain.

However, when a decision-maker's level of satisfaction falls below the accepted minimal level, and their uncertainty level exceeds their threshold of uncertainty tolerance, they will choose the *Inquiry* strategy. This indicates that the decision-maker is unsatisfied and uncertain and needs to find a better solution to meet their needs. They will seek interesting opportunities used by peers who are not necessarily close (weak links).

On the other hand, when a decision-maker's level of satisfaction falls below the accepted minimal level, and their uncertainty level is below their threshold of uncertainty tolerance, they will choose the *Optimization* strategy. This behavioral strategy is chosen by those who are unsatisfied but quite certain and, therefore, are open to any available opportunity and all possible behavioral options.

The conceptual framework of the *ENERGY Pro* model incorporates micro and macro-driven factors (Figure 4. 5). Micro-level factors are represented by individual characteristics (socio-demographic and dwelling) of households that affect their satisfaction and uncertainty levels and, ultimately, the choice of a Consumat behavioral strategy. Behavioral options include different ways of adopting or not adopting EER. Adoption or non-adoption decisions impact households’ characteristics as well as households’ characteristics affect their decisions. It creates a feedback loop in the system. In turn, macro-level factors are represented by some global variables that influence all households but to a different extent. Also, households’ decisions affect macro-level factors by contributing, on average, e.g., to increasing or reducing carbon emissions.

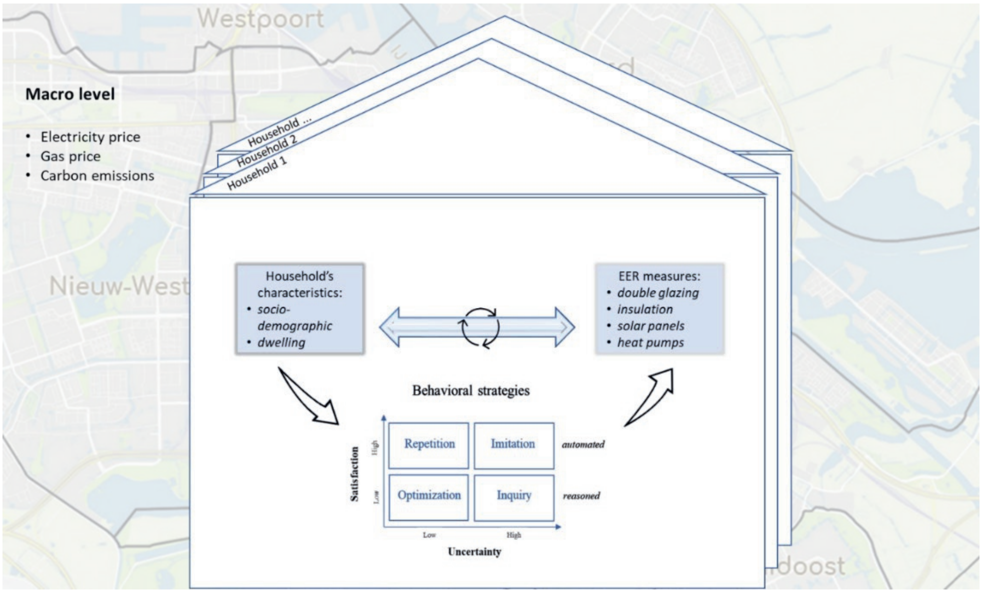

Figure 4. 5. A conceptual overview of the decision-making process in the ENERGY Pro model

Consumat parameters

The model calculates several parameters based on the Consumat, including the level of need satisfaction and behavioral control (BC).

Level of need satisfaction

In accordance with the Consumat meta-model, agents evaluate their need satisfaction which is a product of all need categories and ranges between 0 and 1. Weights of need categories depend on agents' values for each (some need categories might be more important than others, and it differs for each consumat). This study considers the need categories equally important for all households and assigns a similar weighting factor for both needs. This assumption is made to simplify the model and due to a lack of data. The level of need satisfaction for this model is calculated based on the following formula that is adapted for this study from the Consumat [8]:

$$LNS = LNSe^{0.5} \times LNSs^{0.5}$$

LNS refers to the level of need satisfaction. A household is satisfied when its LNS is above the minimum level defined by LNS_{min} (the minimal level of need satisfaction that differs across all households). In this study, the proxy for LNS_{min} is the level of life satisfaction (Table 4. 1). LNS_e and LNS_s are the level of existence need satisfaction and the level of social need satisfaction, respectively. The level of existence need satisfaction represents the ability of a household to meet its annual energy demand (Table 4. 1), taking into account its disposable annual income (Table 4. 1), and is calculated as the following:

$$LNSe^{0.5} = (income - energy\ costs)^{0.5} \text{ , where}$$

$$energy\ costs = elect.cons \times elect.price + heat\ cons \times gas\ price$$

As LNS ranges between 0 and 1, the difference between income and energy costs must be rescaled before exponentiation. For this purpose, we use the *income-cat* variable (Table 4. 1) and assign its categories to a number on a scale between 0 and 1 (more precisely, assign "less than 21,000", "21,000-30,200", "30,200-42,600", "42,600-59,500", and "more than 59,500" to 0, 0.25, 0.5, 0.75, and 1, respectively). Then, we allocate the difference between income and energy costs to one of the values in the abovementioned scale accordingly. After that, the value can finally be exponentiated to the power of 0.5.

While the income variable remains constant throughout the simulation period, the consumption of electricity and gas/heat will change every time step for different reasons (e.g., previously adopted measures or increasing energy prices can cause energy demand reduction). Electricity and gas prices are global variables; while the prices are known for the first two years of the simulation period, they fluctuate over the rest of the time due to uncertainty. As such, the prices are known and set for 2021 and 2022. In 2023, the government introduced energy price caps (maximum tariffs) for the following usage ceilings: 0.40 euros per kWh up to 2,900 kWh of electricity used and 1.45 euros per m^3 up to 1,200 m^3 of natural gas used [157]. The price cap scheme was introduced to help households with soaring energy prices. During this time step, the model determines whether these price caps are relevant. If households exceed the energy consumption ceilings (electricity or gas, or both), the energy amount within these ceilings will be charged according to the price caps, while the excess will be charged with the energy price accounting for price uncertainty.

The energy price uncertainty ranges between 0 and 1 and is normally distributed with a default mean of 0.2 with a standard deviation of 0.1. The price uncertainty can be determined at the beginning of the run time and can be increased or decreased. The price uncertainty with a mean up to 0.4 will have a standard deviation of 0.1, while with a mean above 0.4, the standard deviation will increase to 0.2, and finally, with a mean of 1, it will increase to 0.4. This condition is introduced because, with the higher uncertainty, there is a higher increase in energy price.

After the price uncertainty is determined, the energy price for each following time step (starting from time step 2) is calculated. As such, the electricity price in every new time step is a value from the previous time step taken as a mean with a standard deviation calculated as a fraction of price uncertainty and the previous value of the electricity price. The gas price in every new step is calculated similarly but with a higher standard deviation (a fraction of price uncertainty multiplied by 4 and the previous value of the gas price) because gas naturally has a higher price than electricity and, thus, will increase by a higher fraction.

The level of social need satisfaction represents the relationship between a household's social identity or cohesion (Table 4. 1) and the adoption of the same product by a similar neighbor – *same-product* (the condition is checked in the model). The *social identity* variable is divided by 10 before the initialization, so it ranges between 0 and 1, saving the model's running time. The *same-product* variable is assigned a value of either 0.5 (if the condition does not hold) or 1 (if the condition holds). The social need satisfaction is calculated as the following:

$$LNSs^{0.5} = (social\ identity \times same\_product)^{0.5}$$

LNS plays a central role in determining behavioral strategies that households want to follow. When households are satisfied, they will engage in automatic processing (repetition or imitation) and skip the next time step. In contrast, dissatisfied households engage in reasoned processing (optimization or inquiry) and start the new round following all Consumat steps.

Uncertainty

The choice of households on behavioral strategy from automatic or reasoned processing will depend on their *uncertainty level*. In the *ENERGY Pro* model, an agent's uncertainty is represented by the probability of moving out (Table 4. 1), which is a proxy ranging between 0 and 1 with an increment of 0.25. As this probability might change within a decade, we added some noise with normal distribution and a standard deviation of 0.05 to this value. Also, the uncertainty of agents depends on energy price uncertainty that is global and similar for each household. As such, households' uncertainty is calculated in the model as a sum of their personal uncertainty and energy price uncertainty:

$$U = agent's\ uncertainty + energy\ price\ uncertainty$$

A household is uncertain when its uncertainty level is above the uncertainty tolerance. Uncertainty tolerance is normally distributed with a mean of 0.5 with a standard deviation of 0.1. The mean is taken as 0.5 as the Netherlands scores 53 (in the range between 0 and 100, where 100 is large) at the Uncertainty Avoidance dimension of culture theory by Hofstede [158].

Behavioral control

Behavioral control is a difference between abilities and resource demand. The primary ability to adopt EER includes the legal rights to do so (only owners can adopt). Another ability is the availability of financial resources – wealth (Table 4. 1), while resource demand includes the availability of EER products (which we assume are available in the market) and their prices (Table 4. 2). After checking the ownership of a household, behavioral control is calculated as the difference between financial ability and a price for a measure that has not been adopted yet as the following:

$$BC = wealth - \ product\ price$$

Households' abilities influence what behavioral options are available and largely determine whether they can satisfy the needs. The fact that households can adopt the measures only when they have sufficient funds and legal rights prevents them from continuously investing in adopting EER whenever they remain unsatisfied. If the behavioral control of a household is smaller than 0, the consumption of an opportunity is impossible. The higher the BC, the easier consumption of the opportunity becomes. In addition, if a household's energy bills represent a high percentage of its income (more than 10%)[29], it cannot afford to invest in EER. Thus, households encountering this condition make only a "repeat" decision. If the behavioral control is positive, households update their memory. In its memory, the agent keeps track of its knowledge and experience of adopted measures and the information of the agents in its social network. Agents update their memory only in reasoned mode, therefore, when they make their decisions on a behavioral strategy, they choose between optimization and inquiry. Accordingly, if the behavioral control is negative, agents choose a strategy of the automated mode – repetition or imitation.

Memory

In this model, memory value starts from 0.1 as all households are assumed to hear and know the general information from media about climate change, energy crisis, energy transition, etc. In addition, the households have their own beliefs about it; however, there is a lack of data with regard to this factor. Thus, to incorporate the initial beliefs of households, the value in the range of 0 and 1 with an increment of 0.1 is assigned to each household randomly. The memory also increases by 0.2 in two cases: either if a household adopted any measure already and presumably has information and experience in it or when a household interacts with a similar neighbor and receives information about the neighbor's experience. In the latter case, the impact of interaction (having contact with a similar neighbor) should be at least 0.5, which means there is an information exchange. Finally, when it reaches 1, the memory resets to the sum of the initial value of 0.1 and the initial belief value (different for each household). In the model, this reset function is called "forget-old-information" and is used to reduce the impact of old information. Households do not adopt if their memory is lower than 0.5, meaning they do not have enough information.

The similarity of households is based on location, age, and income (Table 4. 1). Location is a neighborhood (Dutch: wijk) where a household resides. There are 99 neighborhoods in the city of Amsterdam (5 neighborhoods out of which are dropped based on the analysis of their

[29] This means a household is unable to afford adequate access to energy services necessary for basic energy needs.

representativeness). Households also check their similarity based on the age category. In this study, age refers to the age of a representative of a household who undertook the survey (overall, there are 7 age categories). The last aspect that is checked for the similarity between households is income. In this case, we use the income-cat variable with 5 categories, and if households fall under the same household income category, they are considered similar.

Synthetic population

The synthetic population was created using the spatial microsimulation method and R package *ipfp,* known for its computation speed and simplicity [150]. Spatial microsimulation involves sampling rows (observations) of survey data to generate lists of individuals for geographic zones that expand the survey to the population of each geographic zone considered [159]. While most publicly available census datasets are aggregated, and individual-level survey data with geographical details are unavailable for confidentiality reasons, this method overcomes the challenge by combining census and survey data to simulate geographically specific populations (Figure 4. 6).

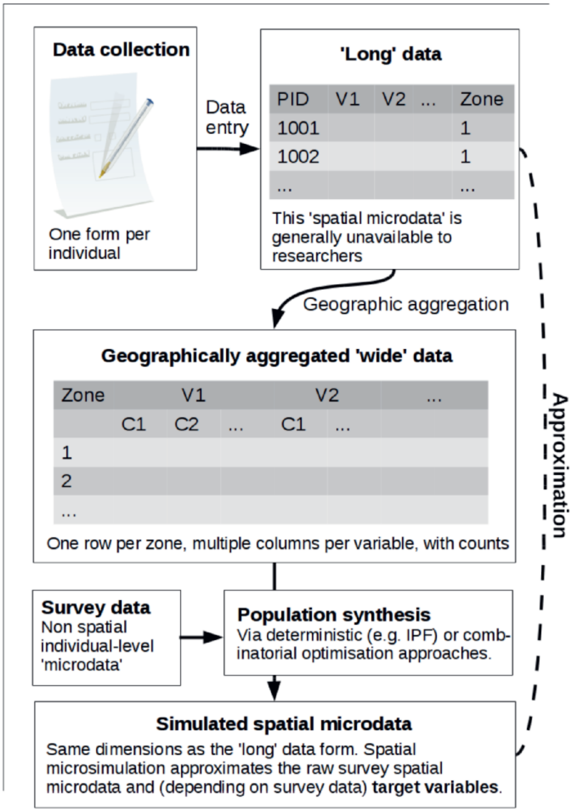

Figure 4. 6. Schematic of population synthesis [160]

In this study, we use the Iterative proportional fitting (IPF) technique, which is one of the key techniques in spatial microsimulation [159]. This technique enables the calculation of the maximum likelihood of the presence of given individuals from survey data in specific zones based on census data. In other words, the method allocates all households from the sample survey to each small area and then reweights each household for each small area. The IPF algorithm is implemented using the following formula [150]:

$$w_{i,z,t+1} = w_{i,z,t} * \frac{cons_{z,v,ind_{i,v}}}{\sum_{j \in I} w_{j,z,t+1} * I(ind_{j,v} = ind_{i,v})}$$

In this formula, I represents the set of households, Z – the set of zones (i.e., neighborhoods), V – the set of variables, and C_v – the set of categories for variable $v \in V$ (e.g., income categories).

The matrix *ind* is a two-dimensional array (based on survey data) where each row $i \in I$ represents a household and each column $v \in V$ a variable. As such, the value of the cell $ind_{i,v}$ is the category of the household i for the variable v. Then, a three-dimensional array *cons* (based on census data) represents constraining count data: $cons_{z,v,c}$ is the number of households corresponding to the marginal for the neighborhood $z \in Z$ (e.g., neighborhood Gein), in the variable $v \in V$ (e.g., household income) for the category $c \in C_v$ (e.g., income category "30,200-42,600"). Given the example, this means that $cons_{z,v,c}$ denotes the total number of households in the neighborhood Gein with annual income ranging between 30,200-42,600 euros. In this study, constraint variables are household income, household compositions, dwellings' construction year, and living area size. These constraint variables are selected following the previous studies' findings on factors affecting the adoption of EER measures [76], [92], [94], [100].

$I(ind_{j,v} = ind_{i,v})$ is the indicator function that checks the condition whether the category of the variable v for the household j (i.e., any household in the set I) is the same as the category of the variable v for the household i (i.e., specific household in the set I being considered in the current iteration). The indicator function outputs 1 if the condition is true and 0 otherwise. This is a process of selecting only those households j that share the same category as the household i for the given variable v. The sum in the denominator is over all households j in the set I. As $ind_{i,v}$ is the category of the household i for the variable v, the denominator corresponds to the sum of the actual weights of all households having the same category in this variable as i. The weights are redistributed such that the data follows the constraint concerning this variable.

Finally, the weight matrix $w(i,z,t)$ determines how representative each household is of each neighborhood with i corresponding to the weight of the household in the neighborhood z during the step t (i.e., iterations over constraints). However, the IPF generates fractional weights making it difficult to use the results as a final table of agents needed as input for an

ABM. Therefore, converting the fractional weights into integers with a minimum loss of information is important before we use it in the *ENERGY Pro* model.

The "Truncate, Replicate, Sample" (TRS) integerization method is one of the probabilistic methods that has proven to be more accurate than other methods (i.e., deterministic) [159]. This method constrains the maximum and minimum integer weight resulting from integers just above and under each fractional weight based on probability [160]. The TRS consists of three steps: (1) *truncate* all weights by keeping only the integer part, (2) *replicate* agents by considering these integers as the number of each type of agent in the zone, (3) *sample* according to the probability of an agent to appear in the zone.

The next step after integerization is validation. The validation of the created synthetic population included the following goodness-of-fit measures: fit between constraints and estimates based on a correlation coefficient (also for each neighborhood), distribution of households based on their household size categories per district, comparing the number of districts and neighborhoods created with the census data, and standardized absolute error (i.e., relative error). We conduct several evaluation measures to ensure the validity of the dataset created.

To evaluate the fit between constraints and estimates and their correlation for each neighborhood, we used Pearson's coefficient *r* as it is the most commonly used measure of aggregate level model fit for internal validation [150]:

$$r = \frac{\frac{1}{n}\sum_{i=1}^{n} x_i y_i - xy}{\sqrt{\frac{1}{n}\sum_{i=1}^{n} x_i^2 - x^2}\sqrt{\frac{1}{n}\sum_{i=1}^{n} y_i^2 - y^2}}$$

This formula corresponds to the covariance divided by the product of the standard deviation of each vector *x* and *y* (observed and estimated). If both vectors have the same values and the covariance is equal to the product of the standard deviation, the *r* coefficient is then close to 1 and the fit is perfect. This measure is sensitive to outliers in the vectors, which means if only one category has a bad fit, the *r* value is very affected, and therefore, should be reliable.

Another evaluation we undertook to validate the dataset is measuring standardized absolute error, also called relative error *RE* [150]:

$$RE = \frac{TAE}{P * n\_var} = \frac{\sum_{ij} |obs_{zc} - est_{zc}|}{P * n\_var}$$

The RE is the proportion of the total absolute error *TAE* to the product of the total population *P* and the number of variables *n_var*. *TAE* is the sum of errors based on observed *obs* and estimated *est* values for each constraint category *c* and each neighborhood *z*.

Based on these tests, we omitted five neighborhoods (out of a total of 99) and one district (Westpoort) from the analysis that did not pass the validation due to a lack of data in the survey. The details concerning the goodness-of-fit measures and their outputs are offered in Table A4. 2 and Table A4. 3 in Appendix.

Data imputation

After creating the synthetic population, there are still some missing values for three variables: electricity consumption (12% missing), gas consumption (12% missing), and landlord (8% missing). We impute the data to avoid omitting the observations with unknown values and biases caused by them. Data imputation is a process of replacing missing data with an estimated value based on other available information. Imputing the data with about 10% missing values is acceptable. To impute the data, we use R package *mice*. After all missing values have been imputed, the data can be treated and analyzed following standard approaches for complete data.

Initialization

The initial state of the model is determined by the input files, which include geospatial data on residential buildings, household characteristics, and information on various EER measures. The number of households and dwellings remains the same in all runs; their allocation to buildings is based on location, dwelling type, and construction year. Due to the lack of precise household coordinates, households may be assigned to different buildings within a neighborhood each time the model runs, depending on the random seed. Each cell is shared by several buildings. Additionally, the model sets initial electricity and gas prices, as well as carbon emissions, for the year 2021.

Input Data

After initialization, this model does not input further external data.

4.3. Sensitivity experiments

4.3.1. OFAT sensitivity analysis

In this study, we use the one-factor-at-a-time (OFAT) method to explore the model's behavior and examine its sensitivity to changes in factors. We selected four factors for the analysis (Table 4. 3). Given the stochastic nature of the model, it is necessary to conduct multiple runs to examine whether randomness (i.e., random seed) affects the model output. Therefore, each factor's change is analyzed from an average of 20 iterations with random seeds to reduce possible stochastic effects. We examine how changes in selected factors affect the number of adoptions across EER measures as well as the choice of the Consumat strategies in different districts. In this section, we demonstrate and discuss an example of Zuidoost and compare it with other districts different in their contexts. The results of the sensitivity analyses of the rest of the districts are offered in Appendices.

Table 4. 3. Factors used for the OFAT sensitivity analysis

Factors	Description	Scenarios
Electricity price	Change in electricity price (±15 cents per kWh)	0.082, 0.232 (base), 0.382
Gas price	Change in gas price (±40 cents per m^3)	0.429, 0.829 (base), 1.229
Mean of energy prices' uncertainty	Change in the mean of energy (electricity and gas) prices' uncertainty	0.1, 0.2 (base), 0.3, 0.5, 0.7
List of similar neighbors	Change in the list of similar neighbors (original list based on location, age, and income; original list constrained additionally by education; removed age constraint from the original list; removed income constraint from the original list)	The original list (base), constraint_educ, remove_age, remove_income

Electricity price

Figure 4. 7 shows the effect of an electricity price change on adopting EER measures and behavioral strategies choices in Zuidoost. The output shows the sensitivity of the model to electricity price changes[30]. The adoption rate of EER measures varies depending on the electricity prices, with a higher number of measures being adopted when prices are reduced. The most significant differences in adoption rates are observed in the cases of double glazing and heat pumps. In terms of the chosen strategies by homeowners in Zuidoost, there is more variation with electricity price changes in the number of *optimize* and *inquire* strategies, with more of these strategies being chosen under the lower electricity price.

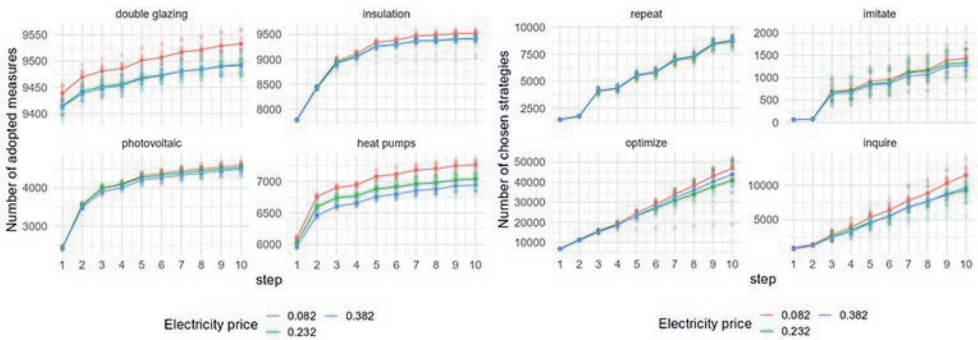

Figure 4. 7. Sensitivity of model outputs (left: uptake of EER measures; right: behavioral strategies choice) based on the varied electricity prices in Zuidoost

The model sensitivity differs in the case of other Amsterdam's districts, even though the pattern of the EER uptake remains similar. In the case of Oost (Figure 4. 8), the adoption of

[30] It should be noted that the scale of the number of adoptions differs across the four EER measures; therefore, the adoption output of each measure should be carefully interpreted.

double glazing and heat pumps is higher when electricity prices are lower, similar to Zuidoost. Although the difference appears more significant when comparing these two districts, it's essential to consider their varying scales when interpreting the results. However, regarding insulation and solar panels, the change in electricity prices has minimal impact on their uptake in Oost. The model output on chosen strategies in Oost is also sensitive to electricity price changes; however, it does not have a clear price scenario that would lead to a distinct output.

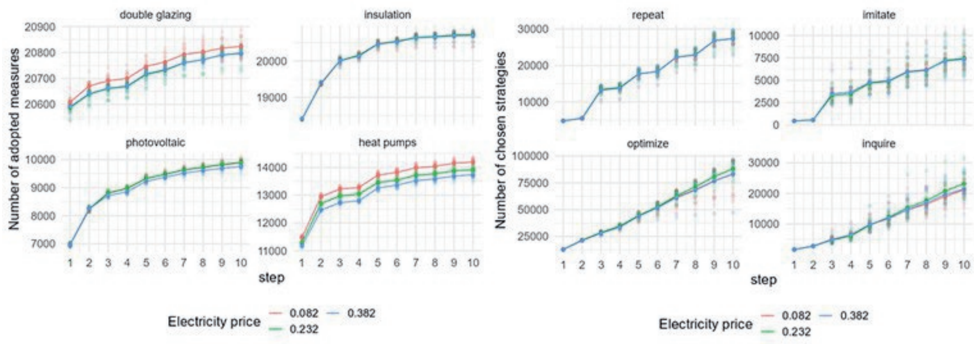

Figure 4. 8. Sensitivity of model outputs (left: uptake of EER measures; right: behavioral strategies choice) based on the varied electricity prices in Oost

Another district that shows sensitivity to electricity price changes is Zuid (Figure 4. 9). Zuid is a larger district in terms of its population, and also in terms of the number of adopted measures. The pattern of the EER uptake in Zuid is similar to the patterns of the previous two districts. However, the number of chosen strategies slightly differs from the earlier examples. There are more homeowners that *optimize* under the lower electricity price, while fewer of them choose to *inquire*.

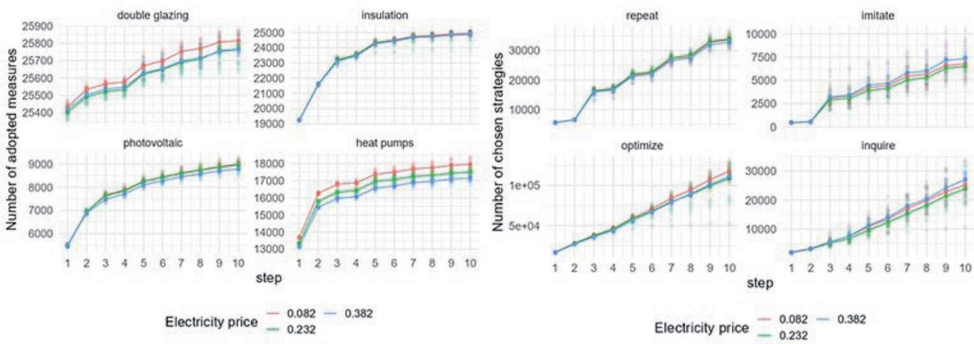

Figure 4. 9. Sensitivity of model outputs (left: uptake of EER measures; right: behavioral strategies choice) based on the varied electricity prices in Zuid

Gas price

Figure 4. 10 shows a gas price change's effect on adopting EER measures and behavioral strategies choices in Zuidoost. The adoption rate of the EER measures changes with the change in gas prices. As such, the model is the most sensitive to the changes in gas prices in terms of double glazing and heat pump uptake. The number of these two measures is increasing (to a different extent, though) with a lower gas price. In terms of behavioral strategy choices, there are some slight differences in the output. The differences concern the number of chosen *optimize* and *inquire* strategies, becoming more visible at the time step 6 (the year 2027) under the lower gas price.

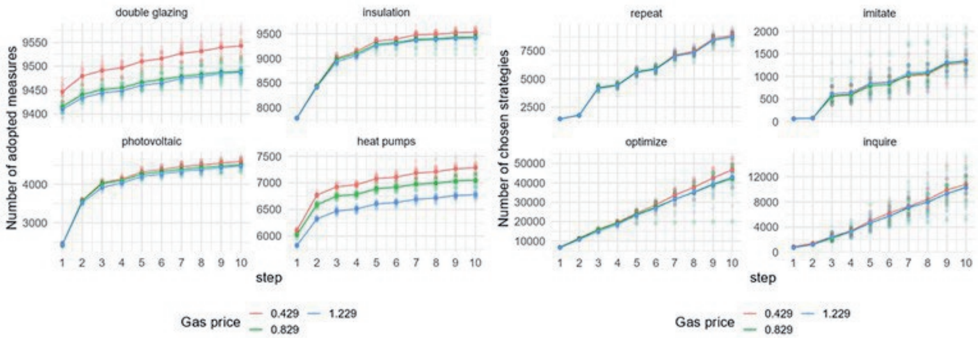

Figure 4. 10. Sensitivity of model outputs (left: uptake of EER measures; right: behavioral strategies choice) based on the varied gas prices in Zuidoost

Similarly, in the case of Oost, when it comes to the adoption of double glazing and heat pumps, the model is particularly responsive to fluctuations in gas prices, showing high levels of sensitivity (Figure 4. 11). On the other hand, when the gas prices decrease, the difference in the adoption of double glazing in Oost is less pronounced. Regardless of how much gas prices change, the number of chosen strategies remains almost the same under all examined scenarios. Similar patterns of the model output have been observed in the case of Zuid (Figure A4. 5).

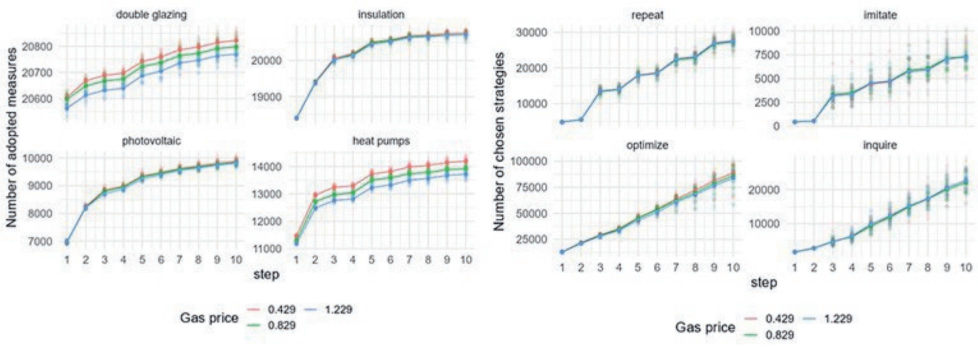

Figure 4. 11. Sensitivity of model outputs (left: uptake of EER measures; right: behavioral strategies choice) based on the varied gas prices in Oost

Mean of energy prices' uncertainty

Figure 4. 12 shows the effect of a change in the mean of energy prices' uncertainty on the adoption of EER measures and behavioral strategies choice in Zuidoost. The model outputs are sensitive to a change in the mean of energy prices' uncertainty. In general, the adoption of all EER measures is increasing with lower energy prices' uncertainty, which means that the more certain the prices are, the more EER measures homeowners adopt. The change in the mean of energy prices' uncertainty also affects the behavioral strategy choice. The number of *repeat* or *optimize* strategies chosen by homeowners increases with a lower mean of energy prices' uncertainty, which aligns with the Consumat framework. With a much higher number of performed *optimize* strategy compared to the *repeat* strategy, the model output indicates a higher number of EER adoptions. In contrast, a higher mean of energy prices' uncertainty implies more homeowners choosing to imitate or inquire. This means that with higher uncertainty, homeowners perform their strategy considering the behaviors of others. Similar patterns of the model sensitivity to the change in the mean of energy prices' uncertainty are observed in Zuid (Figure A4. 5).

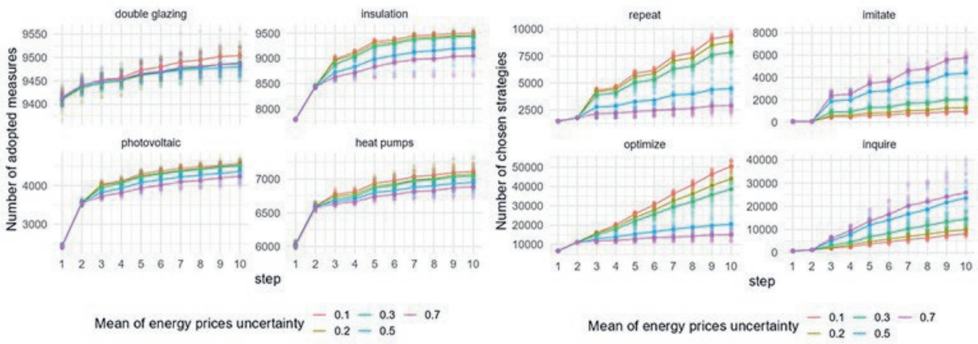

Figure 4. 12. Sensitivity of model outputs (left: uptake of EER measures; right: behavioral strategies choice) based on the varied mean of energy prices' uncertainty in Zuidoost

The model output based on the varied mean of energy prices' uncertainty is slightly different for the case of Oost (Figure 4. 13), though the pattern of the uptake is similar to the pattern that observed in other districts when varying this factor. In Oost, there is no observable difference in the uptake of all EER measures under two uncertainty levels – 0.1 and 0.2. Also, homeowners choose to *inquire* more under the highest level of uncertainty examined, which is different for other districts.

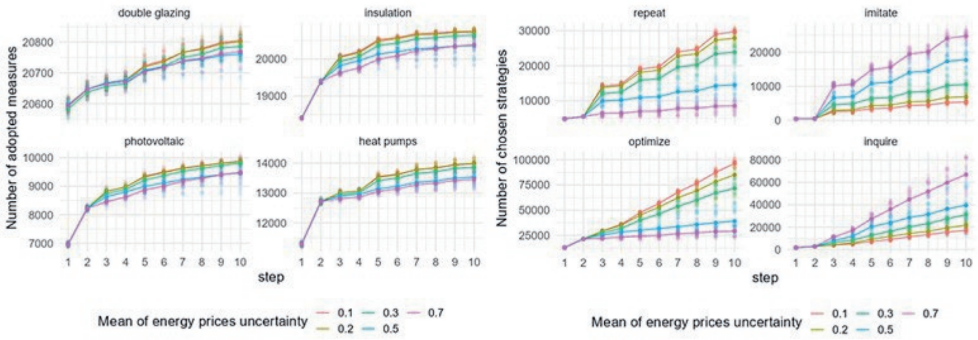

Figure 4. 13. Sensitivity of model outputs (left: uptake of EER measures; right: behavioral strategies choice) based on the varied mean of energy prices' uncertainty in Oost

Chapter 4

List of similar neighbors

Figure 4. 14 shows the effect of a change in the list of similar neighbors on the uptake of EER measures in Zuidoost. We examined two scenarios removing one constraint at a time (age – "remove_age" and income – "remove_income") and adding one constraint (education – "constraint_educ"). Removing constraints expands the list of similar neighbors with whom homeowners interact while adding a constraint shortens this contact list. The model output is sensitive to a change in the list of similar neighbors. The output shows that interacting with more similar neighbors (based on location, age, income, and education level) increases the adoption of all EER measures. In contrast, expanding the similar neighbors' list decreases the EER adoption rate. Under both scenarios, the difference is larger for double glazing and heat pump adoption.

The change in the list of similar neighbors also affects the behavioral strategy choice. The output shows that homeowners choose one of the reasoned strategies under the scenarios when homeowners interact with more similar neighbors (base and constraint_educ). As the reasoned strategies imply adopting the measures, the list of more similar neighbors is the best option for the EER uptake. In contrast, with the expanded similar neighbors' list, homeowners choose one of the automated strategies, such as *repeat* and *imitate*. Similar results of the EER uptake and chosen strategies based on the varied list of similar neighbors are observed in Oost (Figure A4. 6).

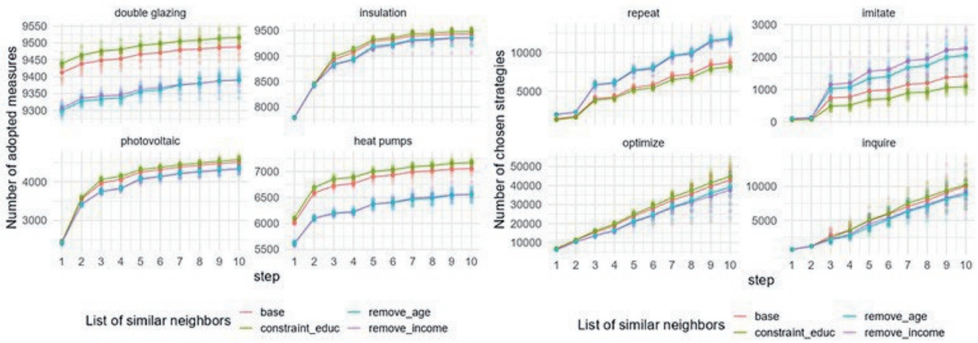

Figure 4. 14. Sensitivity of model outputs (left: uptake of EER measures; right: behavioral strategies choice) based on the varied list of similar neighbors in Zuidoost

Sensitivity of the model outputs in Zuid is marginally different compared to other districts (Figure 4. 15). This difference is caused by the difference in the population size of the districts, in general. That is, the patterns observed in Figure 4. 14 and Figure 4. 15 look similar, but should be interpreted differently as their scales differ. Additionally, it is interesting to notice that when homeowners interact with similar neighbors based on location and age, the uptake of double glazing and heat pump is slightly higher than when they interact with similar neighbors based on location and income.

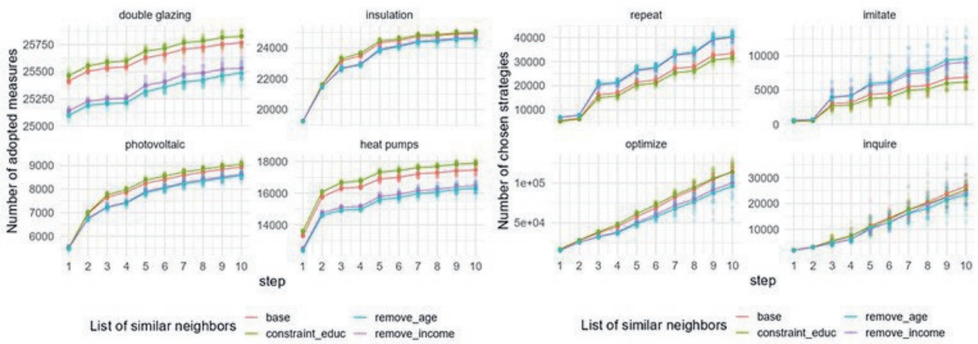

Figure 4. 15. Sensitivity of model outputs (left: uptake of EER measures; right: behavioral strategies choice) based on the varied list of similar neighbors in Zuid

In summary, based on the sensitivity analysis, it is evident that changes in factors' values affect the model output. The results of the sensitivity analyses across the rest of the districts show various model patterns in terms of the EER uptake and behavioral strategy choice that can be found in the Appendices. Overall, the obtained results from the sensitivity analysis allowed us to explore the model's behavior and potential outputs under the scenarios varying one factor at a time.

4.3.2. Interaction experiment

In addition to the OFAT method that enables exploring and understanding the model's behavior, examining possible interaction effects is useful [161]. One of the commonly used methods for testing the interaction is a standardized linear regression [162]. However, the *ENERGY Pro* model is limited to 10 time steps, which does not allow for producing enough output to examine it in the regression. Therefore, in this study, to examine the existence of interactions in the model, we simply vary two factors at a time. It is a quick-and-dirty way of studying the output and gaining more insights into the model's behavior.

To explore the interaction, we vary electricity and gas prices and examine their interaction effect on the EER uptake. Figure 4. 16 demonstrates the effect of the interaction of gas and electricity price changes on the EER uptake in Zuidoost. This experiment shows that the highest uptake of double glazing, heat pumps, and solar panels occurs under the scenario when the electricity price is reduced by 15 euro cents per kWh and the gas price is reduced by 40 euro cents per m^3. Additionally, there might be high uptake of solar panels under the base gas price and lower electricity price (reduced by 15 euro cents). This also holds for the case of insulation adoption rate. It can also be noticed that there are less favorable uptake scenarios under the electricity price increase by 15 euro cents per kWh. Overall, there are multiple different energy price change scenarios under which the EER uptake can potentially be high in Zuidoost.

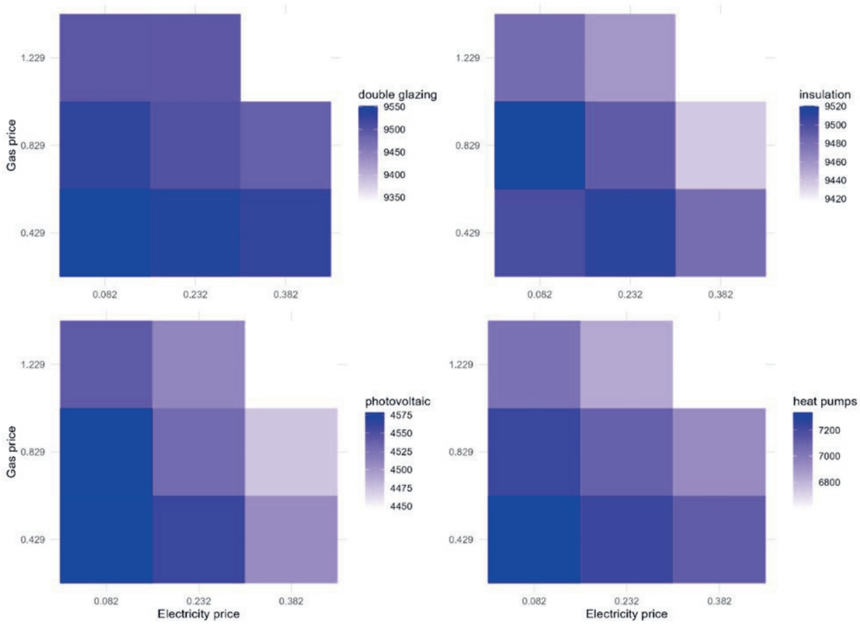

Figure 4. 16. The effect of the interaction of gas and electricity price changes on the EER uptake in Zuidoost

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In contrast, there are less scenarios that are favorable for the EER uptake in Oost in general (Figure 4. 17). In the case of this district, there are more scenarios of lower EER uptake under the higher gas price that increases by 40 euro cents per m^3, whereas the Zuidoost example shows that this occurs under the highest electricity price with an increase by 15 euro cents per kWh. The highest adoption rate of double glazing, insulation, and heat pumps might be under the lowest tested electricity and gas prices that are reduced by 15 euro cents per kWh and 40 euro cents per m^3, respectively. However, in terms of solar panels, the highest adoption rate is feasible with the base electricity price and lower gas price (reduced by 40 euro cents).

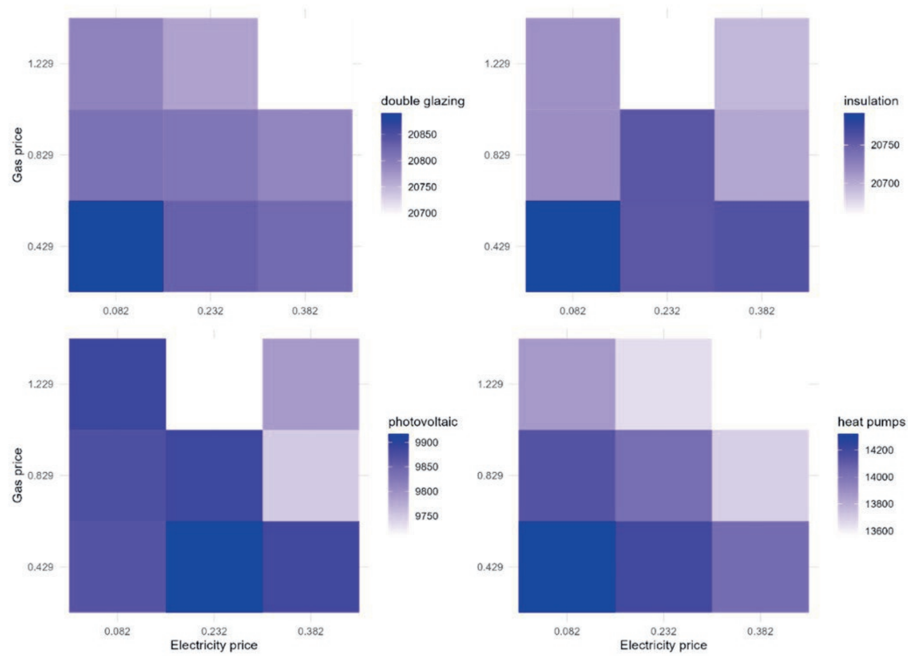

Figure 4. 17. The effect of the interaction of gas and electricity price changes on the EER uptake in Oost

In Zuid, there are even less scenarios that are favorable for the EER uptake (Figure 4. 18). The highest rate of the EER uptake occurs under the lowest electricity and gas prices in this district (reduced by 15 euro cents per kWh and 40 euro cents per m^3, respectively).

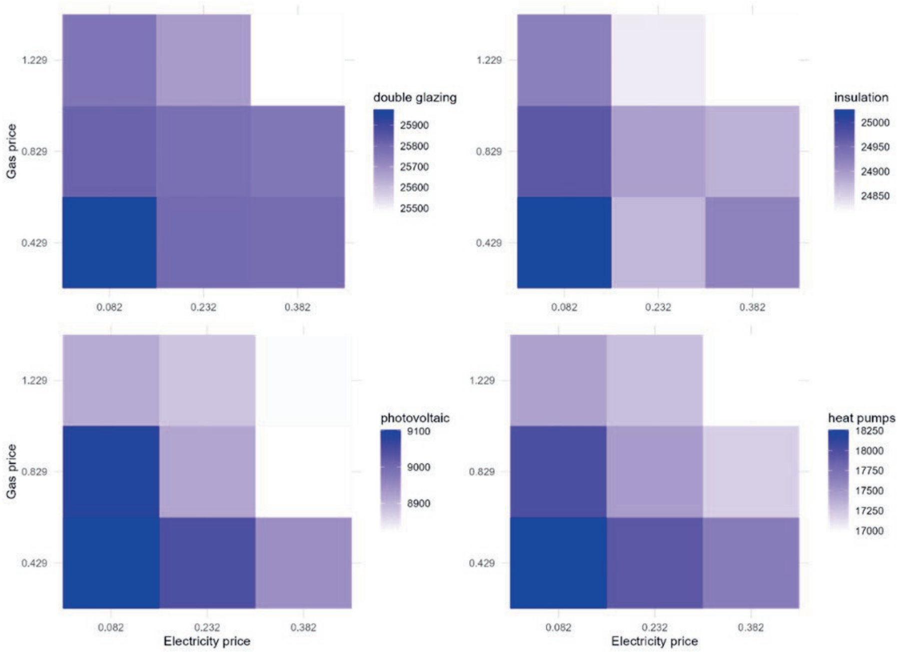

Figure 4. 18. The effect of the interaction of gas and electricity price changes on the EER uptake in Zuid

This interaction experiment provides additional insights on the model behavior and can also be useful for designing potential policy interventions taking into account the contextual differences of the districts. The interaction experiments results of the rest of the districts can be found in Appendix. We did not conduct other interaction experiments varying two factors as this is not as accurate to examine the existence of interactions as it could be when using the regression analysis.

4.4. Model calibration and validation

4.4.1. Model calibration

Calibrating the model for the simulation period of 2021-2030 is a challenging task since it involves projecting into the future. As such, it is difficult to obtain calibration data that reflects the actual conditions of the simulation period. Despite this challenge, having access to relevant data can help partially calibrate the model. Satellite images for PVs in Amsterdam can be one of the important sources for calibrating this model. However, the difficulty arises from the absence of satellite images beyond 2021. This issue underscores the importance of the government's attention to the matter. Access to data would facilitate research and enhance the accuracy of policymaking. A possible solution is to mandate annual reporting from homeowners-adopters on the measures taken, if any. Nonetheless, it is essential to recognize that the model's projections are subject to uncertainties and should be interpreted with caution.

4.4.2. Model validation

This study heavily relies on expert validation, given the specificity of the model's simulation period discussed above. The process of expert validation involved interviewing energy experts[31]. The experts participated in a structured interview process that involved several steps. Firstly, they were presented with a general question regarding their expectations for the uptake of the four EER measures. Secondly, they were asked to reflect on the factors they believed were the most important for driving EER uptake. Thirdly, they were shown a model simulation and asked to evaluate whether the outputs were consistent with their expectations. Fourthly, they were asked to consider the results of sensitivity experiments. Fifthly, they were asked to reflect on potential differences in EER uptake across different districts. Finally, each expert was asked to propose policy interventions that could be instrumental in accelerating the energy transition in Amsterdam by 2030. Each expert focused on a specific district in their analysis.

Expectations about the EER uptake

The experts encountered challenges when trying to reflect on their expectations for EER uptake, with only one common expectation emerging among them. Specifically, all three experts agreed that double glazing and insulation were likely to see higher uptake due to their relative ease of adoption in the city. To validate the overall expectations for EER uptake, one of the experts suggested referring to official documents outlining Amsterdam's future vision and expectations for energy transition, such as the Roadmap of Amsterdam [4] and the Heat Transition Vision of Amsterdam [163]. However, these documents were found to lack specific targets for residential EER uptake in the city, focusing instead on broader goals for the energy transition. As a result, it is challenging to form a clear picture of expected EER uptake in Amsterdam.

The most important factors affecting the EER uptake

According to the opinions of the three experts, gas and electricity prices are the most significant factors that influence the uptake of energy efficiency measures. They also point out that energy price uncertainty is closely related to changes in energy prices and can significantly impact households' decision-making. Furthermore, two energy experts stress the significance of social influence, especially that of neighbors, in promoting the adoption of visible measures such as PV. They note that in smaller neighborhoods, people tend to be more closely acquainted, and information can spread quickly through word of mouth. The

[31] Energy experts included a strategic advisor at the Sustainability department of the Municipality of Amsterdam, a senior assistant professor at Wageningen University who previously worked as a researcher at the energy project in Zuidoost district, and a research fellow at Amsterdam Institute for Advanced Metropolitan Solutions.

experts' views support the meaningfulness of the factors chosen for the OFAT sensitivity analyses. Additionally, the experts emphasize that the combination of gas and electricity prices is expected to have a more substantial effect on homeowners' adoption decisions.

The model outputs

The experts found the model outputs to be both meaningful and insightful. During their feedback sessions, each expert concentrated on a specific district, acknowledging the variations in uptake within the areas they examined. They attributed most of these differences to differences in households and dwelling characteristics. The experts further observed that these variations occurred at the neighborhood level, emphasizing the importance of narrowing the research focus to gain a more comprehensive understanding of household decision-making.

During the discussion of the model outputs, the experts raised two points of concern. The first was a higher uptake of heat pumps compared to solar panels in the Centrum district. Two experts noted that the adoption of heat pumps was expected to be the slowest among the four EER measures in this area due to space constraints and the complexity of heat pump installations in the majority of monumental buildings found in Centrum.

The experts also noted a significant uptake of the EER measures in the first time step (the year 2022), which is due to the low level of need satisfaction among homeowners caused by the high LNS_{min} threshold. The model includes a slider that allows for the exploration of different scenarios by adjusting this variable. When the LNS_{min} is lower, the overall uptake of all measures is also lower, particularly the adoption of heat pumps. However, one expert highlighted that the drastic uptake observed in the model may not always be due to the level of need satisfaction among households, but rather to various macro-level factors. Therefore, the model's outputs should be considered alongside other contextual factors to gain a better understanding of the dynamics driving the uptake of EER measures.

On the other hand, two expert who focused on the Centrum district emphasized that the level of need satisfaction is a crucial factor in the adoption of EER measures in this particular area. They noted that the majority of homeowners in Centrum are high-income residents who prioritize their comfort and are willing to invest significant amounts of money to enhance it. Therefore, in the Centrum model simulation, adjusting the LNS_{min} using the slider and observing how it affects the output is meaningful. During the interview, we ran an experiment to determine whether the model output would change and whether it was significant. As anticipated by the two experts, the model output in Centrum was sensitive to a lower LNS_{min}, resulting in a lower uptake of heat pumps and a higher uptake of solar panels, which has reflected reality better.

Sensitivity experiments outputs

The experts have emphasized that sensitivity experiments provide valuable insights into the model's behavior. During the OFAT sensitivity analysis, it was observed that the model is sensitive to changes in all selected variables. However, in the case of energy price changes, the model output was found to be more sensitive to the gas price change, which all experts agree upon. The experts have also unanimously agreed that the gas price is and will remain the most critical factor affecting the adoption rate of EER measures in the Netherlands. Moreover, the experts have evaluated the effect of mean energy price uncertainty on the EER adoption rate, and they find it reasonable. It has been observed that homeowners with less uncertainty tend to adopt EER measures more actively, while they also choose to *repeat* or *optimize* more often. Additionally, experts have noticed an interesting pattern in the adoption rate concerning varying lists of similar neighbors. For reasoned behavior, it matters that the list of similar neighbors is more constrained. This means that the more similar the neighbors are, the more likely homeowners are to adopt the measures. However, for automated behaviors, homeowners tend to consider overall neighbors in their surroundings more than just similar ones.

Additionally, we asked the experts to identify the key combination of factors that would influence EER uptake before presenting the results of the interaction experiment. One of the experts pointed out that the combination of electricity and gas prices was critical in this regard. Subsequently, we demonstrated the output of the interaction experiment, and the experts acknowledged that the findings were significant and reflective of reality. However, the experts cautioned that the interpretation should be made carefully, as the interaction experiment only shows the overall EER adoption value at the end of the simulation period, which is subject to uncertainty.

Differences across the districts

According to all three experts, there are significant differences in EER uptake across the districts in Amsterdam. The experts caution that the results should be interpreted in the context of households' and districts' characteristics. One expert emphasizes that the most critical factors contributing to differences across districts are the type of dwelling, location (part of the city where households live), the number of people with house ownership status in the district, households' income, and available subsidies for EER adoption. The experts also agree that differences exist within districts, and a more detailed investigation at the neighborhood level is necessary for further studies, which would also help to validate the model more comprehensively.

Policy intervention scenarios

We consulted with experts to identify potential policy interventions to explore in the next phase of this research. The experts agreed that some policies should be implemented city-wide, while others should be tailored to the unique context of each district. The experts identified controlling residential gas consumption through a gas tax as the most critical policy intervention for Amsterdam's energy transition. Additionally, they recommended exploring policy scenarios such as providing more subsidies for adopting EER measures and increasing public awareness of their importance. However, the experts cautioned that EER measures are complex and can demotivate households from adopting them. Thus, easing EER adoption regulations and related policies will also be crucial. The experts also emphasized the importance of ensuring that all population groups can participate in Amsterdam's residential energy transition without exclusion.

4.5. Using and adapting the model

The first step when running the model is to select a district we are interested in, using the chooser (1). Second, we adjust the model parameters for the desired analysis (2). The parameters that can be adjusted include the mean of the energy price uncertainty and the standard deviation of the uncertainty of individual owner-occupied households by dragging the sliders. The two monitors show the electricity and gas price changes over the simulation time. It is also possible to switch the collective decision-making of homeowners on PV adoption, the new random seed, the LNS_{min} adjustment, whether only owners make EER decisions or both owners and tenants, and whether multi-apartment buildings consist of only owner-occupied apartments. Some of these parameters are used for sensitivity analysis. After the parameters are set, we load the GIS data with the default settings, including households' socio-demographic and dwelling characteristics of the chosen district (3).

Depending on the districts' population size, the model takes about 7-8 seconds to load the settings. Finally, the model can be run either for the whole simulation time or for one time step using the buttons (4). All the settings can also be removed, and the electricity and gas prices can be set to default values, clearing the previously loaded values based on parameters' adjustments (5). Using the buttons underneath the worldview, one can load distributions of different EER measures' adoption or their average adoption rates. A color palette ranging from red to green is chosen to represent the adoption level, where red means no adoptions are made and green means all measures are adopted. On the right side of the worldview, several monitors demonstrate some of the set characteristics' of the chosen district's population and calculated values (e.g., average electricity consumption per household).

The *ENERGY Pro* model can be adapted for other places and other time periods, as well as can be expanded by adding other energy system elements such as electric mobility. Users should take care to verify and validate the model after making changes. We recommend using R programming language to analyze such a large model as it speeds up and automatizes the process.

Appendices

Table A4. 1. The main global variables

Global variables	Description
Electricity price	Electricity price (2021 and 2022, respectively) = 0.23 and 0.35 euros per kWh. For the rest of the simulation period, the electricity price fluctuates based on price uncertainty
Gas price	Gas price (2021 and 2022, respectively) = 0.83 and 1.63 euros per m^3. For the rest of the simulation period, the gas price fluctuates based on price uncertainty
Uncertainty tolerance	Uncertainty tolerance is normally distributed with a mean of 0.5 with a standard deviation of 0.1
Energy price uncertainty	Starting from 2023, energy prices fluctuate based on uncertainty (between 0 and 1)
Overview strategies	Global lists of the total number of Consumat strategies implemented by: (1) all households, (2) owners, (3) tenants, (4) per time step
Overview investments	Global lists of the total number of four EER measures adopted by: (1) all households, (2) owners, (3) tenants, (4) per time step
Residential carbon emissions (Amsterdam)	Residential carbon emissions in Amsterdam in 1990 and 2021 (tons), according to the consumption approach (sources: RVO, Regional Climate Monitor). Gas carbon emissions (1990): 891,928 Gas carbon emissions (2021): 666,932 Electricity carbon emissions (1990): 407,000 Electricity carbon emissions (2021): 288,748
Residential carbon emissions-saved	The difference in electricity and gas carbon emissions calculated between 2021-2030 with and without EER adoption
Energy emission factor in 2021 (Amsterdam)	Electricity emission factor (ton/kWh) = 0.000315, gas emission factor (ton/m^3) = 0.001785

Table A4. 2. Synthetic population validation: goodness-of-fit measures output

Goodness-of-fit measures	Description	Output
1. Fit between constraints and estimates	Correlation between values of constraints and corresponding simulated values	Correlation = 0.9962695
2. Correlation for each neighborhood	Correlation between values of constraints and corresponding simulated values per neighborhood identifies the representativeness of neighborhoods	Acceptable min. correlation = 0.9. Wijk WK036392 has the worst correlation (cor = 0.8)
3. Number of districts and neighborhoods created	In 2021, there were 8 districts and 99 neighborhoods in Amsterdam	1 district and 5 neighborhoods are omitted: District: Westpoort Neighborhoods: NA's – WK036311 (Nieuw-West), WK036350 (Oost), WK036372

		(Noord); worst correlation – WK036392 (Zuidoost), worst fit – WK036310 (Westpoort)
4. Standardized absolute error (relative error)	Total absolute error is a difference between the observed and simulated population divided by the total population multiplied by the number of constraints	RE = 3.6%
5. Distribution of household size categories per district	Share of different types of households in terms of their size across the districts	The distribution output is offered in the Table A4. 3

Table A4. 3. Distribution of household size categories per district

District	Share of 1-person households		Share of 2-people households		Share of 3(or more)-people households	
	Census	estimated	Census	estimated	Census	estimated
Centrum	62%	62%	23%	26%	15%	12%
Nieuw-West	48%	47%	20%	24%	32%	28%
Noord	47%	47%	20%	25%	33%	28%
Oost	52%	52%	22%	26%	27%	22%
West	56%	56%	23%	27%	21%	17%
Westpoort	**84%**	**17%**	**7%**	**83%**	**9%**	**0%**
Zuid	55%	54%	24%	27%	21%	18%
Zuidoost	54%	53%	15%	23%	31%	24%

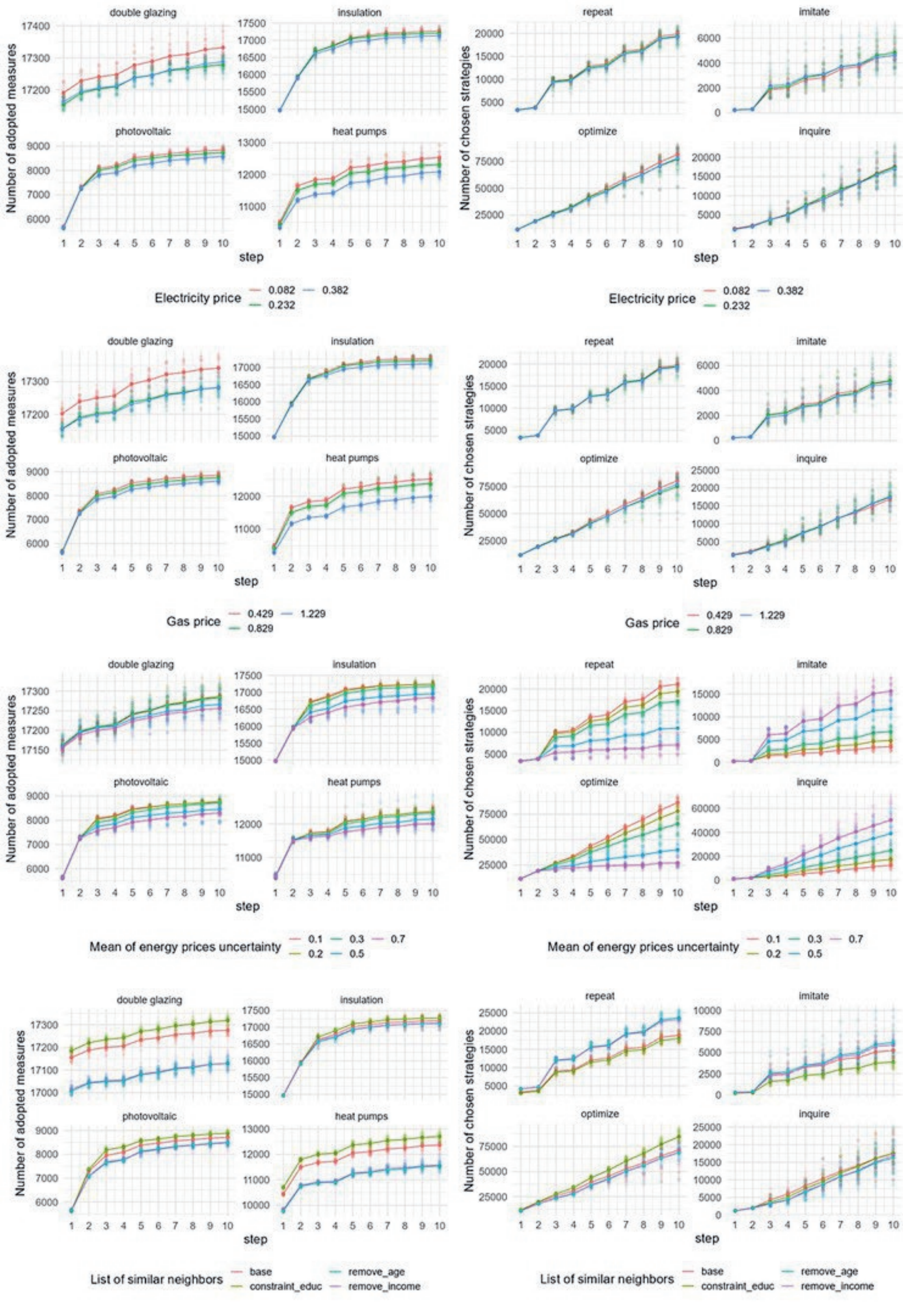

Figure A4. 1. Sensitivity of model outputs based on the varied factors' scenarios in Nieuw-West

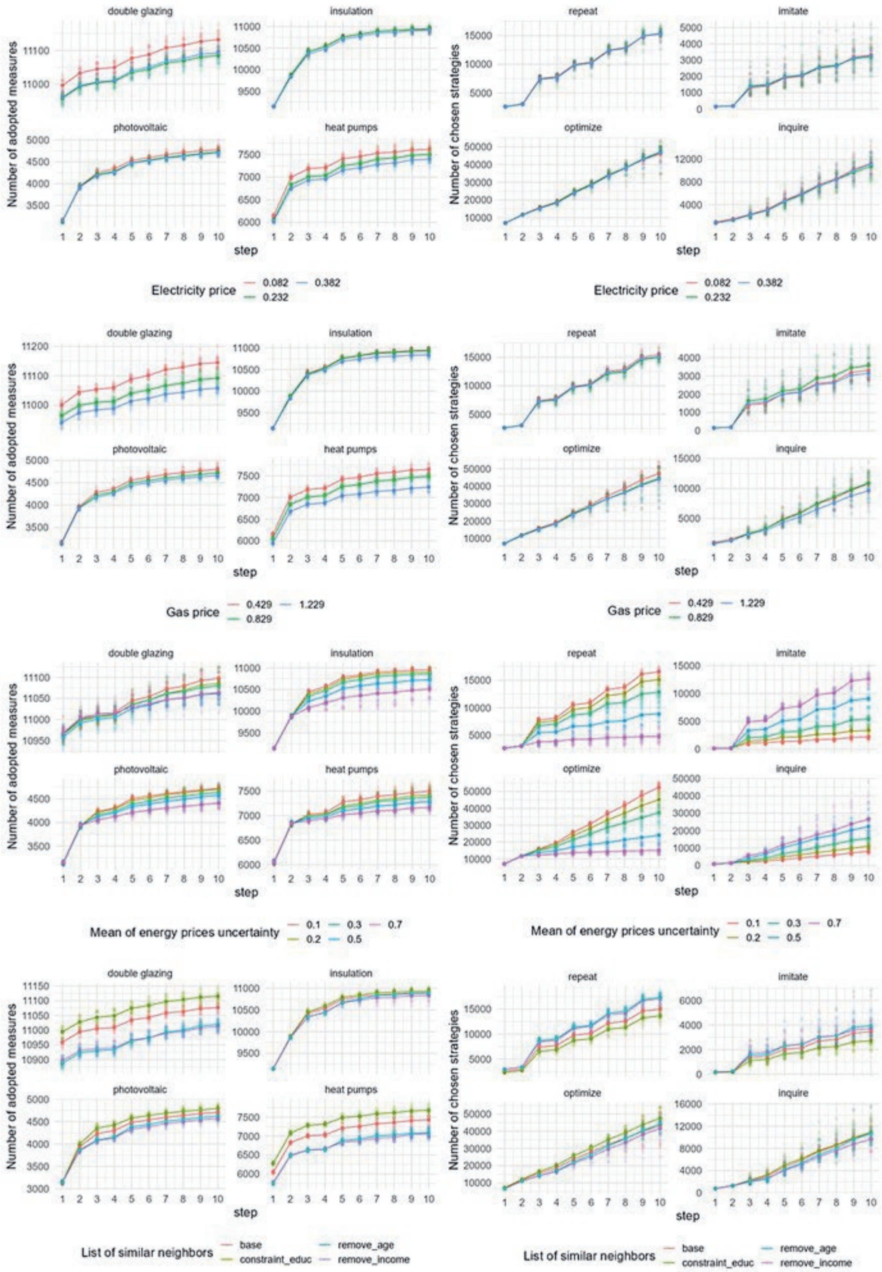

Figure A4. 2. Sensitivity of model outputs based on the varied factors' scenarios in Noord

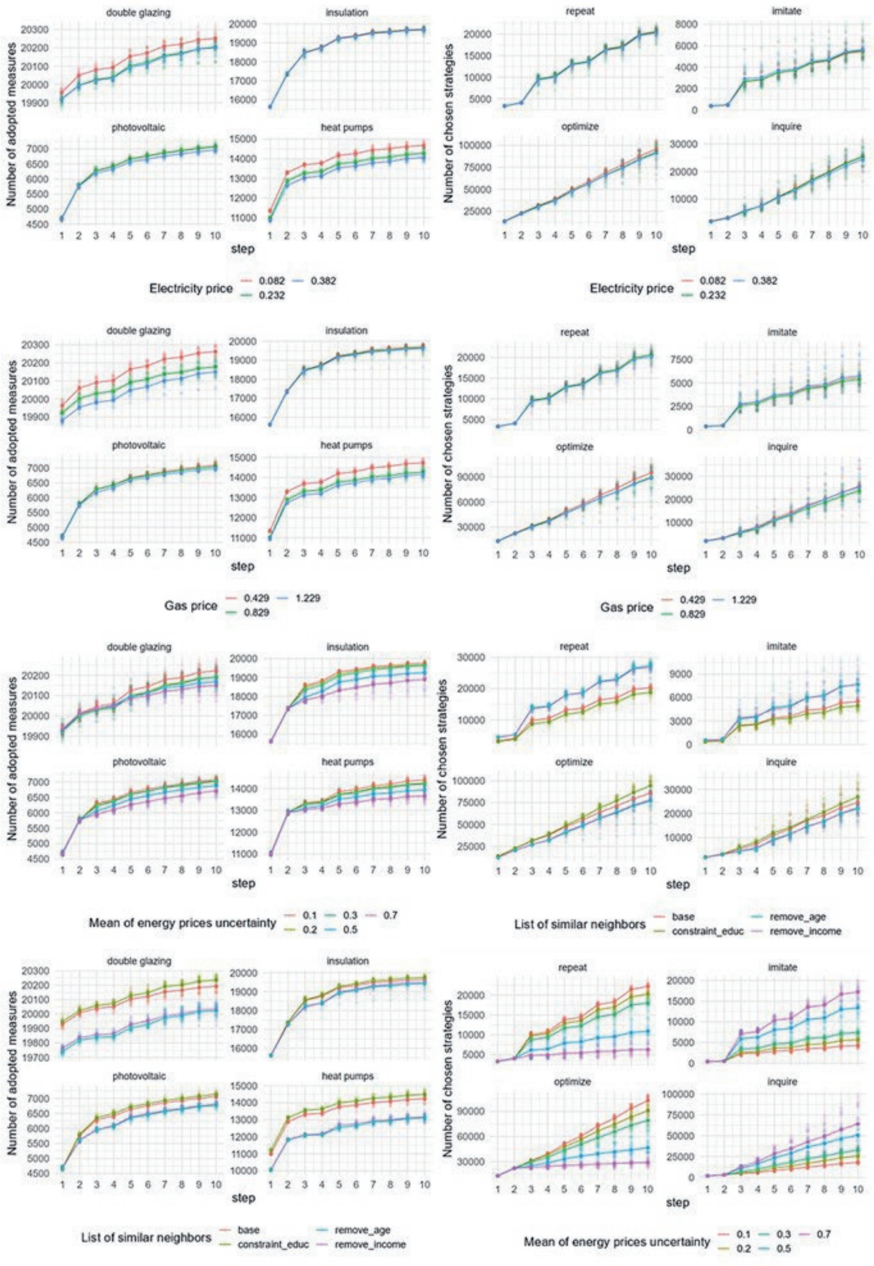

Figure A4. 3. Sensitivity of model outputs based on the varied factors' scenarios in West

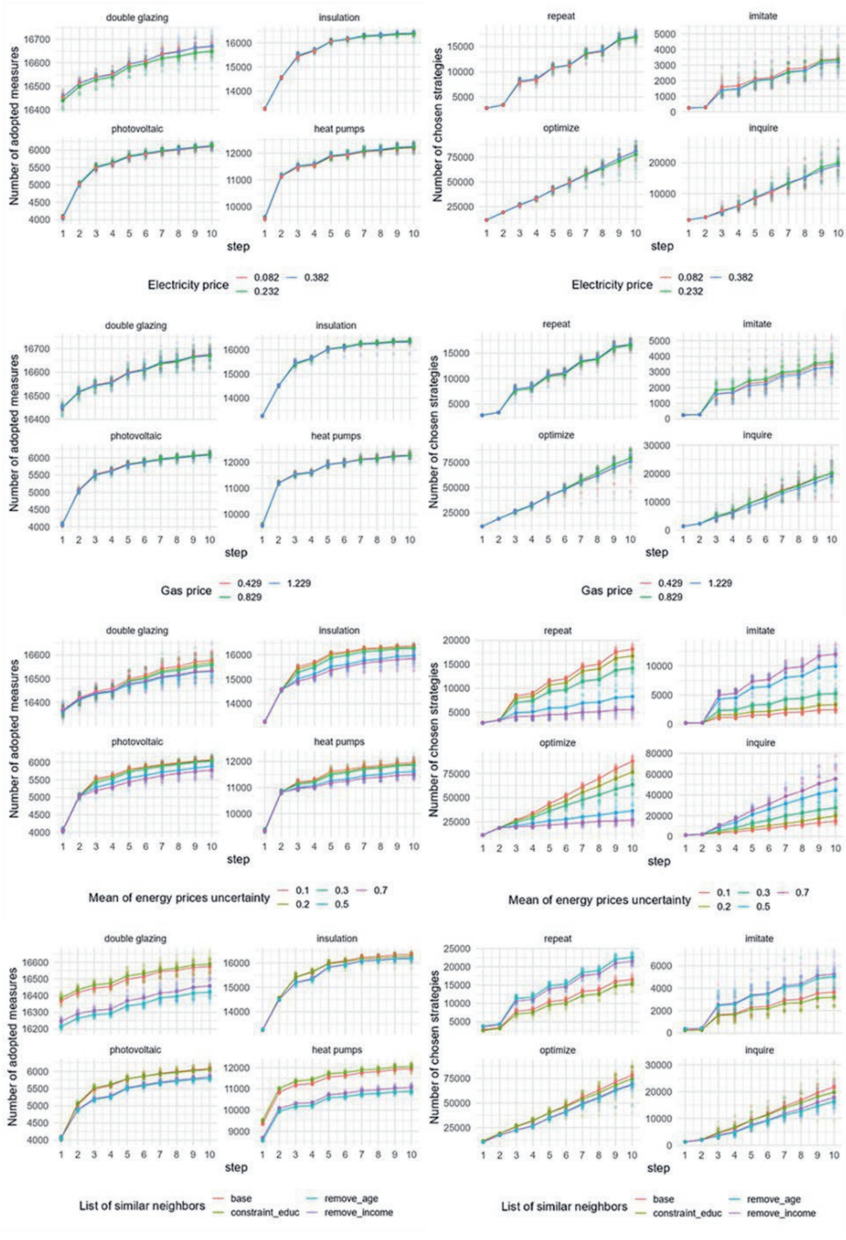

Figure A4. 4. Sensitivity of model outputs based on the varied factors' scenarios in Centrum

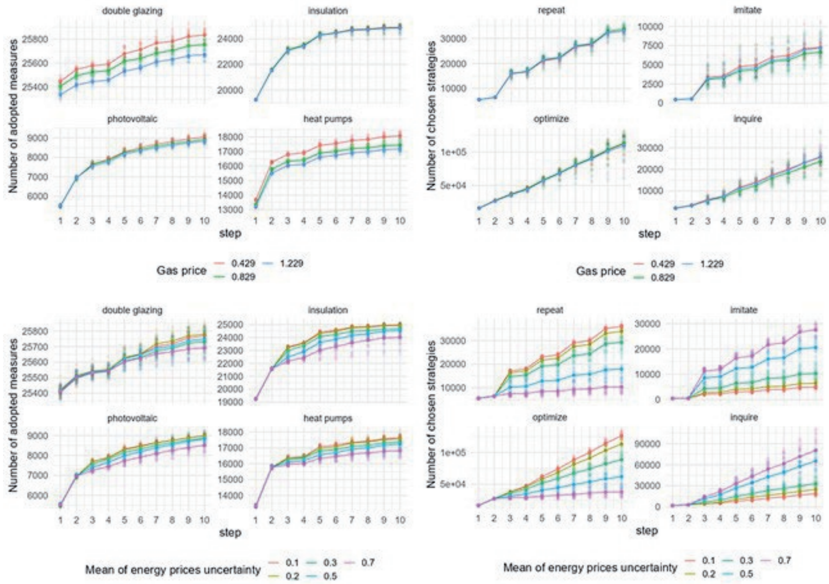

Figure A4. 5. Sensitivity of model outputs based on the varied factors' scenarios in Zuid

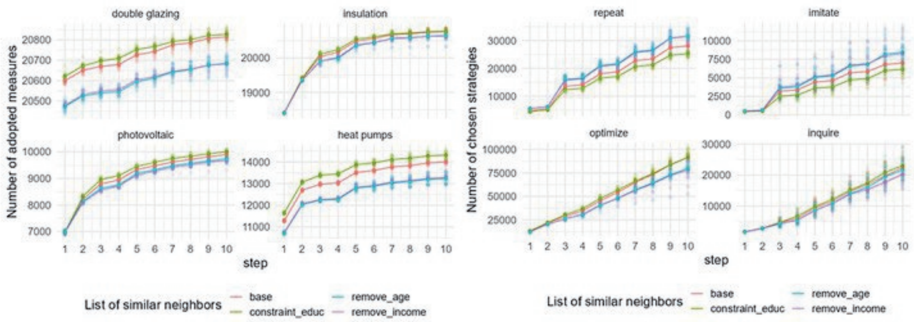

Figure A4. 6. Sensitivity of model outputs based on the varied factors' scenarios in Oost

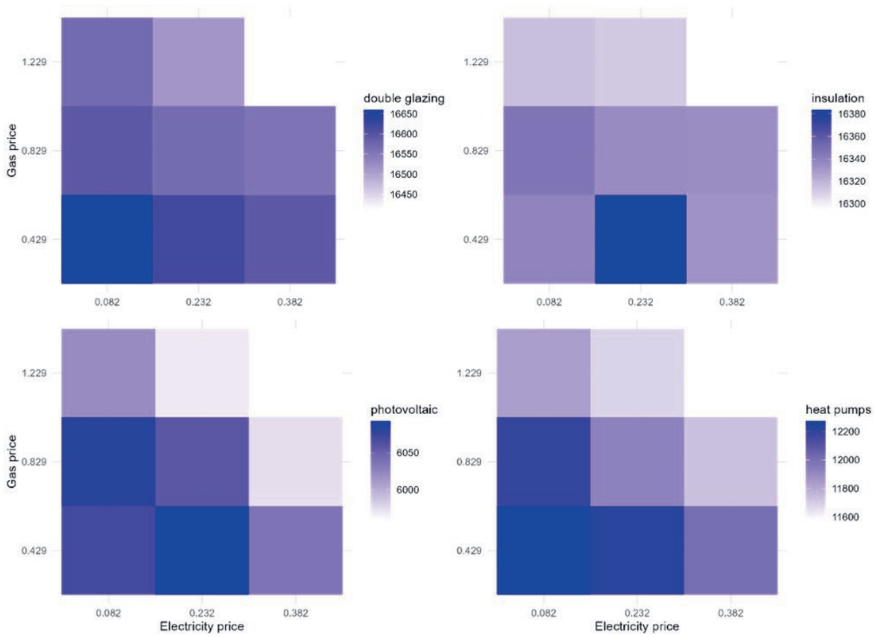

Figure A4. 7. The effect of the interaction of gas and electricity price changes on the EER uptake in Centrum

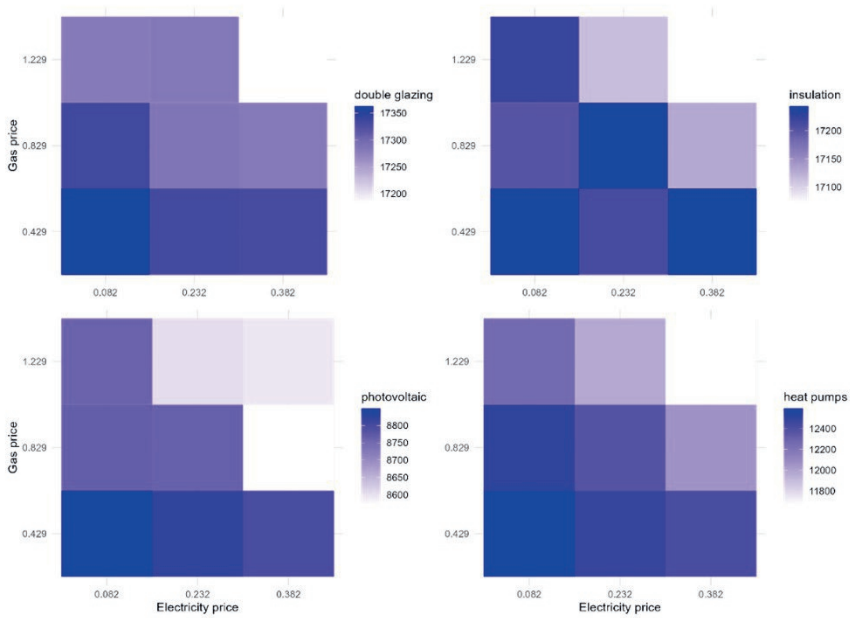

Figure A4. 8. The effect of the interaction of gas and electricity price changes on the EER uptake in Nieuw-West

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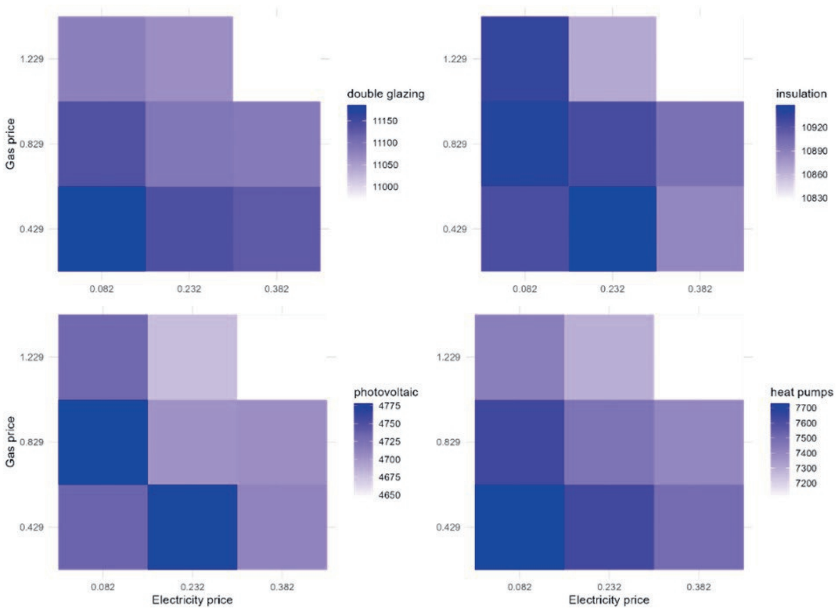

Figure A4. 9. The effect of the interaction of gas and electricity price changes on the EER uptake in Noord

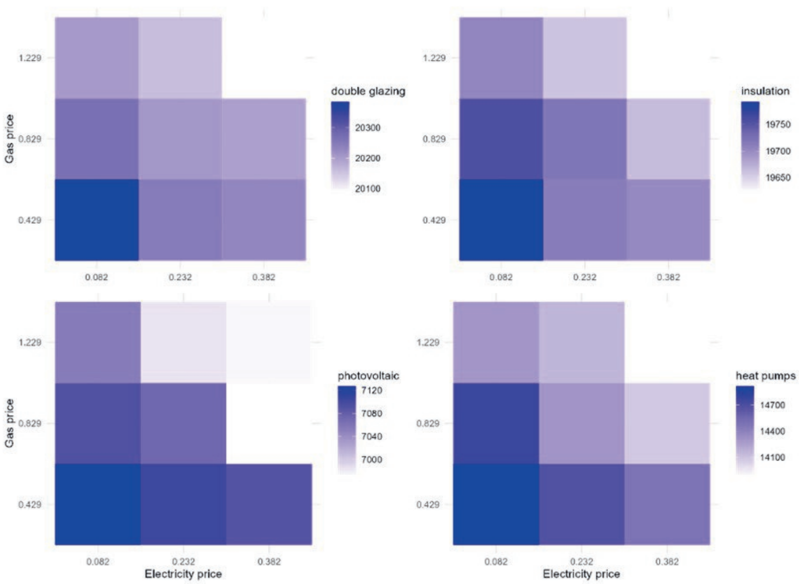

Figure A4. 10. The effect of the interaction of gas and electricity price changes on the EER uptake in West

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Chapter 5

Simulating households' energy transition in Amsterdam: An agent-based modeling approach

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Abstract

Energy efficiency measures and renewable energy are crucial to achieving climate targets and Sustainable Development Goals. Amsterdam is actively working toward these objectives by setting a carbon emissions reduction target and related policies. This study explores how homeowners' energy efficiency decisions contribute to Amsterdam's 2030 carbon emissions goal, using agent-based modeling and spatial microsimulation. We utilize spatial microsimulation to expand the data from the 2021 Dutch Housing Survey, while this generated data is then input into the agent-based model. The key finding stresses the significance of neighborhood-level analysis in energy transition planning due to the importance of contextual differences vis-à-vis energy efficiency decisions. The study also underscores tenants' game-changing role in achieving the target. The model developed for this study can be adapted and used for other places. Based on the insights from the model output, the study proposes policy recommendations that could be a useful addition to the current policy schemes in Amsterdam and similar cities.

5.1. Introduction

There is an increasing urgency to undertake energy-efficient retrofitting (EER) in buildings, to combat climate change, save money, and address gas import shortages in Europe. EER includes measures such as double glazing, insulation of roof, walls, and floor, as well as the adoption of heat pumps and solar panels (i.e., photovoltaic (PV) systems), among others. These measures help to reduce energy usage along with its cost and the carbon footprint of buildings. The concept of Positive Energy Districts (PEDs) has emerged to facilitate the energy transition and contribute to climate neutrality. PEDs are defined as areas that are energy-efficient, self-sufficient, and carbon-neutral [1], in which households play a key role as EER measures adopters and can significantly contribute to the carbon neutrality goal. This commitment has become a priority in achieving the climate targets and the Sustainable Development Goals, particularly, (7) Affordable and Clean Energy, (11) Sustainable Cities and Communities, and (13) Climate Action.

As the traction to achieve PEDs gains momentum across urban areas worldwide, the city of Amsterdam aims to reduce carbon emissions by 55% compared to 1990 levels by 2030 [4]; therefore, 2030 is an important target for transforming energy systems. The scope of this research is Amsterdam, as it is a good example of both urban challenges and opportunities and has the potential to become a leader in innovative energy transition solutions and a beacon for other large cities. This study examines to what extent households in Amsterdam can contribute to the city's CO_2 emission reduction target by achieving PEDs via energy consumption reduction, energy efficiency, and renewable energy generation. More specifically, this study explores how homeowners make EER adoption decisions and how these decisions differ across the city districts in Amsterdam. This study, in particular, focuses on exploring human-centric pathways for the energy transition as the energy system is a complex adaptive system [135] comprising heterogeneous agents living in areas that differ in their context. It accounts for the differences in population abilities and opportunities to meet their energy needs and contribute to the energy transition. Based on this research, designing more effective and area-focused energy transition policies will be possible.

In this study, we use the agent-based modeling (ABM) approach of computational social simulation, with households as agents. This method enables studying the behaviors of heterogeneous agents and their interactions over time in a quantitative manner [125]. Designed for bottom-up analysis, the ABM captures a system's emergent behavior and accounts for system complexity [136]. Employing the ABM, we developed an empirical and spatially-explicit model, "*ENERGY Pro" (*energy *PRO*sumers*)*, at the core of which are the households of Amsterdam [164]. The design of the agents' sociality is based on a theoretical framework *Consumat* that was developed by Jager et al. (2000) based on multiple behavioral theories on cognitive processes and underlying driving factors for behavior [146].

The *ENERGY Pro* model utilizes the BAG[32] (Basisregistratie Adressen en Gebouwen) data [138] and empirical data from the Dutch Housing Survey *WoonOnderzoek Nederland (WoON)* 2021 [139]. The WoON is a nationwide survey[33] that captures socio-demographic and dwelling information, as well as current and desired living situations and energy-related data. Due to a limited number of Amsterdam-specific respondents, we additionally use a spatial microsimulation approach to expand the data by generating a synthetic population of Amsterdam. The created spatial microdata serves as an input into the ABM and enables mimicking Amsterdam's households. The model design can also be applied to other areas.

Even though substantive energy transition-related ABM applications exist, examples of spatially explicit empirically-driven energy models are still scarce [137]. The main reasons for this are data unavailability, the limited grasp of sociality, and the limited capacity of computers to run larger-scale empirical models. First, a lack of data can cause an inaccurate or incomplete representation of agents in the model leading to less realistic model outcomes and can limit the understanding of the dynamics of complex systems [165]. Also, data limitations can hinder the accurate calibration and validation of ABMs, affecting the reliability of the model's results. Second, a lack of theoretical knowledge of sociality hinders researchers from knowing which data are needed, creating relevancy issues [166]. Finally, due to the computers' processing capacity, especially if decision algorithms are sophisticated and much data is used, most energy transition models focus on a smaller scale, such as a district or neighborhood [137]. To conduct a city-scale analysis, explore the differences across the city districts, and examine whether it is possible to achieve the climate goal of the city as a whole, we develop the model for the entire city. We run the simulation for one district at a time to overcome the computer capacity limitation.

Most of the models have rarely explored the adoption of multiple (complementary) technologies [167]. Previous studies usually explored the adoption of individual technologies such as residential solar PVs [145], heating technologies (e.g., heat pumps) [168], or insulation measures [101]. We address this gap by focusing on four EER measures, including double glazing, insulation of walls, roof, and floor, and adopting solar panels and heat pumps. To the best of our knowledge, the *ENERGY Pro* model is the first of its kind: empirical, spatially explicit with the focus on multiple measures, having several layers, and containing both individual and collective decisions. The conceptual framework of this study is offered in Figure 5. 1.

[32] Dutch automated system of Basic Registration Addresses and Buildings.

[33] The survey is conducted every three years and uses a stratified sample taken from all Dutch residents 18 years old and older registered with their local municipality.

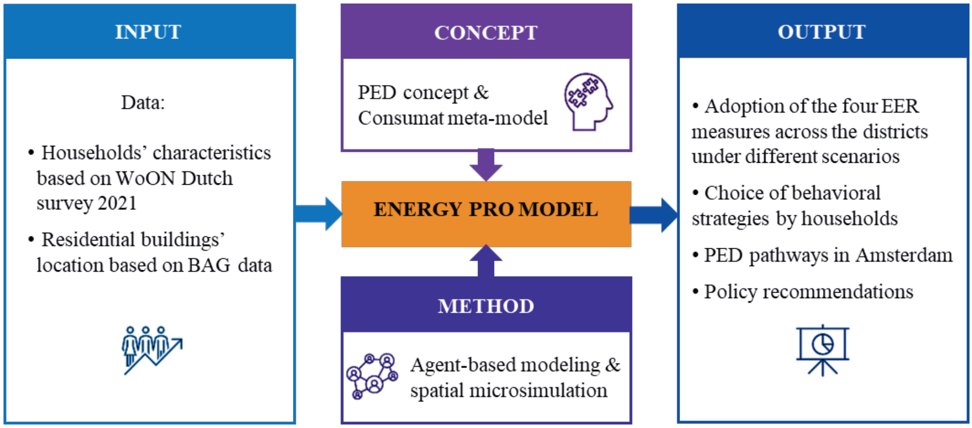

Figure 5. 1. Conceptual framework of this study

The article proceeds as follows. Section 5.2 presents an overview of the relevant theoretical concepts used to explain energy-related behaviors and decisions, highlighting their similarities and limitations, and discusses the meta-model Consumat applied in this research. Section 5.3 describes the model overview, its validation, and sensitivity analyses. Section 5.4 reports the main results of the model based on the baseline and alternative scenarios across selected districts. Section 5.5 interprets the results in light of the research objectives and discusses the implications of the findings for understanding the EER measures uptake and their contribution to achieving PEDs in Amsterdam. Additionally, this section addresses this study's limitations and potential avenues for future research. Section 5.6 concludes the study by highlighting its contributions and offering key PEDs policy implications of the findings for practitioners and policymakers.

5.2. Literature review on theoretical frameworks for studying energy-related behavior

A range of theoretical frameworks attempts to explain energy-related behaviors and decisions. Among those, the most widely used is the Theory of Planned Behavior (TPB) [169], [170] which has been extended based on the Theory of Reasoned Action (TRA). It is one of the dominant socio-psychological frameworks comprising three components – Attitude, Subjective Norm, and Perceived Behavioral Control (PBC) [170] that shape the behavioral indention and are widely used to study pro-environmental behavior. At the core of the TPB are *economically rational* decisions of individuals aiming to maximize their utility given their budget constraints. These decisions are assumed to be based on known, invariant, and consistent preferences, and the utility is often expressed in monetary terms [171]. However, the TPB is limited by its implicit assumptions of deliberative and static decision-making centered on maximizing self-interest.

More recently, it has been remembered that individuals' decisions are not always based on economically rational deliberations [172] but often on *relational rationality* (i.e., being rational from the perspective of the social world in which individuals exist, prioritizing interpersonal relationships) [173]. Empirical studies reveal that individuals' behaviors and decisions often deviate from the assumptions of economic rationality and are not always driven by economically reasoned "optimal choice" but rather influenced by different cognitive shortcuts and biases [174], [175], [176], [177], [178]. Among the theories that aim at explaining altruistic environmental behavior are Value-belief-norm (VBN) theory [179], the Norm Activation model (NAM) [180], the Attitude-behavior-external conditions (ABC) model [181], [182]. They are common in focusing on an altruistic type of individual behaviors and decisions where individuals give up personal benefits for the sake of collective interests.

VBN is a normative theory that combines value and belief systems into internal responsibilities concerning the environment and moral obligations to act pro-environmentally [175]. Similarly, NAM reflects an individual's ascription of responsibility for not acting pro-environmentally, and anticipated pride and guilt lead individuals to behave in line with their personal norms [180]. They feel responsible for delivering a particular behavior when they are sufficiently aware and motivated by their environment [178]. In addition to personal norms and beliefs, and responsibilities that evolve, it is important to consider external conditions (physical, financial, legal, or social) determined by context as they influence behavior by defining available choices and attitude formation, as articulated in the ABC model [175]. These three approaches capture cognitive biases and *irrational* behaviors that are not covered by classical economic theories [176].

Most researchers used the abovementioned theories and models to study energy-related behaviors and decisions. The combination of theories is applied to obtain a more comprehensive view of individuals' behaviors and decisions considering a wider range of variables. For example, in their theoretical review, Wilson and Dowlatabadi (2007) propose an integrated framework of ABC and VBN that emphasizes interaction effects between different personal and contextual variables and behavior-specific features [175]. A more frequently used combination of theories in studying energy-related behaviors is an integrated framework of TPB and either VBN or NAM. Abrahamse and Steg (2009) considered the integrated framework of TPB and NAM to examine the effect of socio-demographic and psychological factors on households' energy use [183]. The study indicates that socio-demographic factors determine energy use, whereas psychological factors cause changes in energy use [183]. The TPB and NAM combined contribute to the extended explanation of energy use and energy savings behaviors. Brosch et al. (2014) focused on integrating TPB and VBN in their framework to examine intentions to reduce energy use [171]. In addition to this combination, the authors argue that consideration of emotional processes – thoughts, feelings, behavioral responses, and a degree of pleasure or displeasure (experienced in situations related to energy conservation) may deepen understanding of energy-related behaviors and decisions [171].

Notably, however, studies of residential energy-related behavioral changes verified by detailed empirical data are rare [178]. Past research on individuals' behavior in relation to the environment reveals mixed findings. While some studies argued that economic incentives are more efficient in influencing behavior than intervening in individuals' consciousness and knowledge, others showed the opposite, highlighting that increasing awareness impacted behavior more successfully than economic stimuli [184]. This highlights the importance of local contextual factors that differ from area to area and need to be considered in developing behavior-influencing strategies. Therefore, the energy behavior-related field requires more comprehensive and yet realistic studies based on empirical data. For this purpose, the more advanced socio-psychological meta-model Consumat is applied in this research.

The Consumat is a comprehensive conceptual model of consumer behavior that was developed by Jager et al. (1999) based on multiple behavioral theories on cognitive processes and underlying driving factors for behavioral change [185]. The Consumat meta-model offers a theoretical framework with macro-level (equal to all individuals) and micro-level (differ between individuals) factors affecting an individual's behavior and a set of behavioral rules for an artificial agent, the *consumat* [185]. The model's authors aimed to develop a generic model with simulation purposes in different fields. However, the approach has not been widely applied in the energy domain yet (only a few studies, e.g. [186], [187], [188]).

At the core of the Consumat meta-model, there are four decision strategies that individuals (in this study, households) choose: imitate, optimize, repeat, or inquire. The choice of a strategy depends on their *satisfaction* and *uncertainty*. Satisfaction and uncertainty are both influenced by social factors, which can vary significantly depending on the type of homeowners and built areas. When consumats, i.e., agents in Consumat, are highly satisfied with their needs, they tend to adopt automated behavioral strategies, such as *repeating* their previous actions or *imitating* similar consumats. On the other hand, when consumats are dissatisfied, they tend to choose reasoned behavioral strategies, which involve *optimizing* their actions to find better solutions or *inquiring* by seeking input from other consumats (with both strong and weak ties) who appear to have satisfying outcomes. The level of need satisfaction (LNS) ranges between 0 and 1 and is calculated based on the following formula that is adapted for this study from the Consumat [8]:

$$LNS = LNSe^{0.5} \times LNSs^{0.5}$$

LNS_e is the level of existence need satisfaction that represents the ability of a household to meet its annual energy demand, while LNS_s is the level of social need satisfaction that denotes the relationship between a household's social identity and the adoption of the same product by a similar neighbor. A household is satisfied when its LNS is above the minimum level of

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need satisfaction defined by LNS_{min}; the level of life satisfaction is taken as a proxy to represent this variable.

Uncertainty plays a crucial role in determining which of these two types of strategies consumats pursue, as each consumat has a unique level of uncertainty about their decisions and the future, as well as a tolerance for risk that influences their willingness to take risks. In this study, households' uncertainty is calculated as a sum of their personal uncertainty and energy price uncertainty. An agent's uncertainty is represented by the probability of moving out, which is a proxy ranging between 0 and 1 with an increment of 0.25. As this probability might change within a decade, we added some noise with normal distribution and a standard deviation of 0.05 to this value. Additionally, the uncertainty of agents depends on energy price uncertainty that is global and similar for each household. A household is uncertain when its uncertainty level is above the uncertainty tolerance. Uncertainty tolerance is normally distributed with a mean of 0.5 with a standard deviation of 0.1. Our method article offers more details on the conceptual meta-model and the calculation of other relevant parameters [164].

5.3. Methodology

The empirical analysis is based on the *ENERGY Pro* model that is built using the combination of agent-based modeling and spatial microsimulation. While an agent-based modeling approach has been used to build the social simulation model on the energy transition of households in Amsterdam, a spatial microsimulation technique was used for generating data to input in ABM.

The detailed model description is offered in our method article [164] that follows the Overview, Design Concept, and Details + Human Decision-making (ODD+D) protocol based on the format of Grimm et al. (2006) [141] and Müller et al. (2013) [142]. Among different simulation approaches, ABM is the primary approach used to quantitatively study the behaviors of heterogeneous agents and their interactions over time among various simulation methods [125]. With a bottom-up approach, ABM enables the understanding of the emergent behavior of individuals, which in turn helps explain complex macro behavior observed in the real world. The ABM's key advantage in researching the energy transition is its capability to capture and account for complexity [136].

There are several other comparative advantages of ABM. ABM allows modeling the individual decision-making processes in a realistic and detailed fashion. This, in turn, enables researchers to uncover the causality of events, not only correlation, as they can be traced to the roots of individual decisions. In contrast, the individual level of decision-making is not represented in optimization or equilibrium models as they are focused on a more macro and aggregated level [10]. Due to its ability to incorporate individual decision-making and social processes, ABM can be a valuable tool in policy design and evaluation [189]. In addition, ABM is a powerful tool for creating explorative (policy) scenarios without the need to specify future targets as in forecasting models. Moreover, it can capture emergent behaviors of systems with top-down and bottom-up causations and decision-making under uncertainty as well as their complexity and real-world variations, which is impossible with, e.g., normative models [10]. In this context, top-down causation occurs when agents dynamically adapt to system-level changes, whereas bottom-up causation refers to system-level changes arising as emergent outcomes of the collective behavior of agents.

5.3.1. Main features of the ENERGY Pro model

The *ENERGY Pro* model comprises two entities – households and EER measures. While households including homeowners and tenants are the main residential energy consumers, only homeowners are entitled to make the EER adoption decisions. Households are defined by their socio-demographic and dwelling characteristics including household size, household income, education, social cohesion, dwelling type, construction year, and energy consumption. The EER is presented by four types of measures in this study that are double glazing, insulation of roof, walls, floor, and heat pumps, and residential solar photovoltaic. These measures share a common feature as a product price that changes over time, but each measure also has distinct characteristics including after-lifetime emissions, energy generation, electricity demand, and saved heat.

The *ENERGY Pro* model is spatially explicit and covers seven districts of Amsterdam. Each cell or patch in NetLogo represents several buildings with their characteristics being aggregated. In this study, we run the model for one district at a time to have a higher resolution of the households and due to the limitations of the computational capacity of regular computers. The temporal resolution of the model corresponds to one year (one time step) covering a period of 10 years (2021-2030), as this study aims to examine how much households in Amsterdam can contribute to the city's carbon emission reduction goal.

Figure 5. 2 presents the *ENERGY Pro* model overview that demonstrates the layers comprising heterogeneous households, different types of residential buildings, and context-wise diverse districts of Amsterdam.

Figure 5. 2. ENERGY Pro model overview

In this model, households make energy consumption and EER adoption decisions annually. Their adoption decisions depend on their ability to afford EER, their level of need satisfaction, and uncertainty, and these decisions are reflected in the adoption rate. Additionally, global variables such as energy prices and uncertainty of energy prices also indirectly affect their decisions as they contribute to their level of need satisfaction and uncertainty. Table 5. 1 depicts the main parameters that are relevant to the analysis of the results.

Table 5. 1. Main parameters of the model

Parameter	*Description*
Electricity price	The price for electricity is only fixed for 2021 and 2022, for the rest of the simulation period it changes based on energy price uncertainty
Gas price	The price for gas is only fixed for 2021 and 2022, for the rest of the simulation period it changes based on energy price uncertainty
Carbon emissions	Carbon emissions based on energy consumption and EER adoption of households
Adoption rate	The adoption rate of households per cell changes based on the number of adopted EER measures over time
Level of need satisfaction	The level of need satisfaction of households changes based on changes in energy consumption, energy prices, and EER adoption
Uncertainty	Uncertainty of agents changes based on energy price uncertainty
Energy consumption	Consumption of electricity and gas changes based on EER adoption
Behavioral control	The ability of households to afford to adopt EER changes based on EER product prices

At each time step, the model performs the following procedures: (1) the model checks the number of time steps left, (2)-(5) updates the characteristics of the environment such as the EER measures' attributes (e.g., price), carbon emissions, energy generated by households, and energy prices, (6) households interact with their similar neighbors, (7) households evaluate their needs, (8) and check if their behavioral control is positive or negative, (9) if their behavioral control is positive (meaning they can satisfy their needs), they update their memory, (10) households choose one of the decision strategies, (11) households evaluate the level of their need satisfaction, (12) and make collective decisions on PV adoption in multi-apartment buildings (if activated in the simulation), (13)-(15) there are more environment updates including the count of investments made and households' characteristics that did not participate in a current time step (reset to their default values from the previous time step). Our method article offers a flowchart of the model's steps and a more detailed process overview [164].

5.3.2. Data generation and analysis

The model comprises two distinct layers, namely the spatial and social layers. The spatial layer represents the residential buildings in Amsterdam, which is informed by the BAG (Basisregistratie Adressen en Gebouwen) data [138]. The social layer represents Amsterdam households, which is informed by the WoON Dutch survey 2021 [11] and Census data [140].

Even though the number of respondents from Amsterdam is limited to 1,630, the WoON data is valuable as it combines the information on socio-demographic and dwelling characteristics of households as well as their energy use characteristics.

Spatial microsimulation

To overcome the data limitation and to build an empirical and spatially-explicit ABM, we used spatial microsimulation to create a synthetic population and expand the data. The created spatial microdata was used as input into ABM, consisting of 447,685[34] households assigned to residences in certain neighborhoods based on their characteristics such that it matches the housing stock of the respective neighborhood [190]. It is a little smaller than the actual number of households, as several non-representative neighborhoods have been removed from the synthetic population dataset to ensure data accuracy.

Spatial microsimulation is a technique that entails selecting sample rows (observations) from survey data to generate lists of individuals for geographic zones, thereby extending the survey to the entire population of each considered geographic zone [159]. Since most publicly available census datasets are aggregated, and individual-level survey data with geographical details are restricted due to confidentiality concerns, this method addresses the challenge by combining census and survey data to simulate populations that are specific to particular geographical areas.

We use the Iterative proportional fitting (IPF) approach that enables the calculation of the maximum likelihood of the presence of given individuals from survey data in specific zones based on census data. This happens based on several constraint variables and by reweighting each household for each area based on their representativeness. In this study, we used four constraint variables such as household income, household compositions, dwellings' construction year, and living area size. The IPF algorithm is implemented using R package *ipfp* based on the following formula [150]:

$$w_{i,z,t+1} = w_{i,z,t} * \frac{cons_{z,v,ind_{i,v}}}{\sum_{j \in I} w_{j,z,t+1} * I(ind_{j,v} = ind_{i,v})}$$

In this formula, $ind_{i,v}$ is the category of the household i for the variable v (based on survey data), while $cons_{z,v,c}$ (represents constraining count data based on census) is the number of households corresponding to the marginal for the neighborhood $z \in Z$ in the variable $v \in V$ for the category $c \in C_v$. $I(ind_{j,v} = ind_{i,v})$ is the indicator function which value is 1 if the condition is true and 0 otherwise. This is a process of selecting only those households j in the set I that share the same category as the household i for the given variable v. Here, the denominator denotes the sum of the weights of all households having the same category in this variable as i. The weight matrix $w(i,z,t)$ identifies how representative each household is

[34] There were 476,008 households in Amsterdam based on Census data in 2021.

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of each neighborhood with i corresponding to the weight of the household in the neighborhood z during the step t (i.e., iterations over constraints). As the IPF generates fractional weights, we use the “Truncate, Replicate, Sample” (TRS) integerization method to convert the weights into integers to make it usable for ABM [159].

The final step of creating a synthetic population is validating its goodness of fit. To ensure the validity of the created dataset, we conduct several goodness-of-fit measures. First, we measure the fit between constraints and estimates for each neighborhood using Pearson’s correlation coefficient *r* [150]:

$$r = \frac{\frac{1}{n}\sum_{i=1}^{n} x_i y_i - xy}{\sqrt{\frac{1}{n}\sum_{i=1}^{n} x_i^2 - x^2}\sqrt{\frac{1}{n}\sum_{i=1}^{n} y_i^2 - y^2}}$$

This formula denotes the covariance divided by the product of the standard deviation of each vector x and y (observed and estimated). If both vectors have the same values and the covariance is equal to the product of the standard deviation, the r coefficient is then close to 1 and the fit is perfect. In this context, an acceptable value of r starts from 0.9. Based on this test, only one neighborhood had r = 0.8, which was omitted from the dataset.

Second, we measure standardized absolute error, also called relative error *RE* [150]:

$$RE = \frac{TAE}{P * n\_var} = \frac{\sum_{ij} |obs_{zc} - est_{zc}|}{P * n\_var}$$

The RE is the proportion of the total absolute error *TAE* to the product of the total population *P* and the number of variables *n_var*. *TAE* denotes the sum of errors based on observed *obs* and estimated *est* values for each constraint category c and each neighborhood z. Based on this test, the RE was estimated at 3.6%, which is an acceptable value.

Finally, the last two tests included evaluating the distribution of households based on their household size categories per district and comparing the number of districts and neighborhoods created with the census data. In total, based on all four goodness-of-fit measures, we omitted five neighborhoods (out of a total of 99) and one district (Westpoort) from the analysis that did not pass the validation due to a lack of data in the survey. More details concerning the goodness-of-fit measures and their outputs are offered in our method article [164].

Validation and calibration

The model’s validation has relied on structured interviews with energy experts in Amsterdam. The experts reflected on the energy transition in a specific district of their choice. They addressed their expectations for the uptake of the four EER measures, reflected on factors they believed were the most important for increasing the EER adoption, and evaluated whether the model's findings met their expectations. The experts also were asked to address the results of the sensitivity experiments and reflect on potential differences across the districts in Amsterdam. Overall, the experts found the model outputs to be both meaningful and insightful. Our method article offers more details on expert validation output [164].

On the other hand, the model's calibration was not conducted due to the model's simulation period projecting into the future and the absence of data, access to which would enable at least partial calibration of the model. Therefore, the model's findings should be interpreted with caution.

Sensitivity analysis

For the sensitivity analysis, we used the one-factor-at-a-time (OFAT) method. In this analysis, we examined four factors that can potentially affect the model's results, i.e., the EER adoption rate and the choice of behavioral strategies by homeowners. The four factors include electricity and gas prices, the mean of energy prices' uncertainty, and a list of similar neighbors with whom the decision-makers are in contact. Due to the stochastic nature of the model, we conducted multiple runs to examine the randomness effect. As such, we analyzed an average of 20 iterations with random seeds to reduce possible stochastic effects. Additionally, we conducted an interaction experiment to examine the impact of variation of two factors, i.e., electricity and gas price changes, on the EER uptake (more details on sensitivity analysis in [164]).

Software

The model is developed in NetLogo 6.3.0. Additionally, the model heavily relies on R programming language (including "ipfp" and "mice" packages) to perform spatial microsimulation, imputation, and sensitivity analysis.

Scenarios

In this study, we examine a baseline scenario and other alternative scenarios. The baseline scenario reflects the current energy system of Amsterdam (based on data from 2021), in which only homeowners make EER adoption decisions including collective decisions on PV adoption. The alternative scenarios comprise lowering the threshold level of need satisfaction and including tenants in adoption decision-making.

5.4. Results

We provide key findings obtained from the *ENERGY Pro* model, including the potential adoption rate of the four EER measures across different districts in Amsterdam by 2030, based on the baseline scenario. Additionally, we discuss households' behavioral strategy choices over the simulation period and the potential impact of the adopted EER measures on energy consumption, energy balance, and carbon emissions. Following the same structure, we present the potential output under alternative scenarios to better understand household energy-related decision-making and highlight any differences in uptake rates. Overall, the model output offers a comprehensive understanding of various possible pathways that Amsterdam can take toward achieving a successful energy transition through PEDs.

5.4.1. Background of the districts

The *ENERGY Pro* model runs the simulation for seven districts in Amsterdam. Due to space limitations, in this section, we offer an overview of the results of the three districts, namely Zuidoost, Zuid, and Oost. We selected these districts because of their contextual differences to demonstrate distinct outputs. The output of the rest of the districts is offered in Appendices (B).

The districts of Amsterdam are distinct in terms of their area and population size as well as the socio-demographic and dwelling characteristics of households. Table 5. 2 offers the main population and household characteristics in the selected three districts. These provide an overview of the differences across the districts and help to better understand and interpret the model results.

Table 5. 2. Main socio-demographic and dwelling characteristics of selected districts in Amsterdam in 2021 based on the synthetic population

Characteristics		Districts		
		Zuidoost	Zuid	Oost
Population (households)	Owners	10,172 (24.4%)	27,537 (33.5%)	21,928 (30.2%)
	Tenants	31,480 (**75.6%**)	54,674 (**66.5%**)	50,728 (**69.8%**)
	Total	41,652	82,211	72,656
Apartment dwellers	Owners	6,541 (21.9%)	21,569 (32.7%)	16,035 (28.1%)
	Tenants	23,319 (78.1%)	44,377 (67.3%)	40,984 (71.9%)
	Total	29,860 (**71.7%**)	65,946 (**80.2%**)	57,019 (**78.5%**)
Non-apartment dwellers	Owners	3,631 (30.8%)	5,968 (36.7%)	5,893 (37.7%)
	Tenants	8,161 (69.2%)	10,297 (63.3%)	9,744 (62.3%)
	Total	11,792 (28.3%)	16,265 (19.8%)	15,637 (21.5%)
Construction year (owners)	older than 1946	0.8%	**66.4%**	24%
	1946-1980	**27.3%**	13.5%	6.7%
	1981-1990	**45.6%**	3.7%	9.9%
	1991-2000	4.7%	2.7%	**16.1%**
	2001-2010	14.1%	8%	**31.3%**
	2011 and later	7.4%	5.6%	12%
Income (owners)	lower 21000	11.3%	6.2%	6.2%
	21000-30200	10.2%	10%	6.3%
	30201-42600	**27.8%**	17.8%	19.4%
	42601-59500	**28.4%**	19.5%	**24.1%**
	59501 and higher	22.4%	**48.5%**	**44.1%**
Age (owners)	24 and younger	1.7%	0	0.2%
	25-34	15.6%	0.4%	16.8%
	35-44	16%	**18%**	**24.1%**
	45-54	**19.6%**	**20.6%**	**24.5%**

	55-64	**18.8%**	**22.8%**	15.8%
	65-74	**18.4%**	15%	12.8%
	75 and older	9.9%	**23%**	5.7%
Education (owners)	low	15.1%	5.2%	8%
	middle	**27.9%**	16.9%	23%
	high	**57%**	**77.9%**	**69%**
Household composition (owners)	single-person	**38.4%**	**35.9%**	33.5%
	couple	**30.9%**	**38.7%**	**32.9%**
	couple with children	21.9%	20.4%	**26.7%**
	single-parent	8.3%	4.3%	6.1%
	other	0.5%	0.7%	0.8%
Contact with neighbors (owners)	totally disagree	2.4%	3.3%	3%
	disagree	15.5%	14.5%	14.9%
	neither agree nor disagree	28.2%	22.2%	27.2%
	agree	37.3%	43.3%	38.8%
	totally agree	16.6%	16.7%	16.2%
	disagree and totally disagree	17.9%	17.8%	17.9%
	agree and totally agree	**53.9%**	**60%**	**55%**
Average consumption (annual)	electricity (kWh)	2,211	2,166	2,175
	gas (m^3)	800	891	644

The district of *Zuidoost* is located in the southeastern part of the city (Figure 5. 3) and is relatively small in terms of its population, which is 41,652 households. 71.7% of the district's population live in apartment dwellings. Almost half of the houses were built between 1981-1990. While 75.6% of the population of the district are tenants, 24.4% are homeowners that make the EER adoption decisions. As the main focus of this study is on the latter population group, we further continue focusing on this group's characteristics. However, it is essential to note that the main landlords of the tenants-occupied residences in Zuidoost are housing corporations constituting 72.4%.

Over half of the homeowners are middle-income households earning between 30,201-59,500 euros annually. Among the homeowners, 56.8% are between 45 and 74, and 57% are highly educated. Almost 70% of the owner-occupied households are families without children (i.e., single-person and two-people households). 53.9% of homeowners are in contact with their immediate neighbors[35]. The average annual electricity and gas consumption is 2,211 kWh and 800 m^3, respectively.

Compared to Zuidoost, the district of *Zuid* is twice as large, with a population of 82,211 households, and is located in the southern part of the city (Figure 5. 3). An even larger number

[35] The variable "contact with immediate neighbors" shows to what extent the homeowners communicate with their neighbors, which also entails exchanging information.

of households live in apartment dwellings, constituting 80.2%. Most dwellings (66.4%) are relatively old and were built before 1946. 66.5% of the population are tenant-occupied households, with fewer landlords being housing corporations (49.8%) compared to Zuidoost, while 20.5% of landlords are private people.

Almost half of the homeowners in Zuid are high-income households earning higher than 59,500 euros annually. More than 60% of the homeowners are between the age of 35-64, and 23% of homeowners are at the age of 75 and older, which is a relatively large age group of homeowners compared to other districts in Amsterdam. Also, a relatively large share of homeowners in Zuid is highly educated, constituting almost 80%. In Zuid, an even larger number of owner-occupied households is families without children (i.e., single-person and two-people households) compared to Zuidoost and other districts, being almost 75%. Also, a larger share of homeowners is in contact with their immediate neighbors 60% compared to other districts in the city. The average annual electricity and gas consumption in Zuid is 2,166 kWh and 891 m^3, respectively.

The district of *Oost* is located in the eastern part of the city (Figure 5. 3) and has a population of 72,656 households. Similar to Zuid, the majority of the population lives in apartment dwellings (almost 80%). While almost half of the residential buildings are relatively new and built between 1991-2010, a third of the dwellings were newly built between 2001-2010. 69.8% of households are tenants, with more than 50% of tenant-occupied houses being part of housing corporations.

In Oost, almost 70% of homeowners are upper-middle or high-income households whose annual average income is 42,601 euros or higher, as well as 70% of the homeowners are highly educated. The homeowners in this district are relatively younger compared to Zuidoost and Zuid, constituting almost half of the homeowners aged between 35-54. Almost 60% of owner-occupied households in Oost are couples and couples with children. Similar to Zuidoost, 55% of homeowners are in contact with their immediate neighbors. The average annual electricity and gas consumption is 2,175 kWh and 644 m^3, respectively, while the gas consumption is lower in Oost compared to Zuidoost and Zuid due to the newer residential built environment.

Figure 5. 3. Selected districts on the map of Amsterdam in 2021 [191]

5.4.2. Model output based on the baseline scenario

The baseline scenario of the simulation model is based on the households' characteristics in 2021, the Dutch energy system (i.e., energy prices, EER adoption rights) following the local regulations, and the assumptions made about the individual and collective decision-making and Consumat parameters (e.g., uncertainty tolerance of Dutch households). The baseline scenario is described in more detail in the method article [164].

Potential EER adoption rate

The key output of the *ENERGY Pro* model is the adoption rate of the four EER measures by homeowners by 2030 in Amsterdam. Figure 5. 4 shows the visual output of the simulation in the Zuidoost district. The results reveal that double glazing and insulation of walls, roof, and floor are likely to be the most adopted measures by homeowners by 2030. As such, we observe the adoption rate of these two measures varying on average between 60-80% in most areas except for two neighborhoods, while some cells have a 100% adoption rate. The two neighborhoods lagging in adopting these measures are "Holendrecht/Reigersbos" and "Driemond" located in the southern and western parts of the district, respectively.

In contrast, the uptake of solar panels is the lowest among other EER measures in Zuidoost, with the adoption rate mostly varying between 0-20%, with the lowest average rate in the previously-mentioned two neighborhoods. The other two neighborhoods, "Bijlmer Centrum" and "Gein", located in the north-western and south-eastern parts of the district, respectively, show a relatively higher rate of solar panels adoption. In terms of heat pumps, the adoption rate is lower than it is for double glazing and insulation but higher than it is for solar panels, with the same two neighborhoods (i.e., "Holendrecht/Reigersbos" and "Driemond") lagging behind.

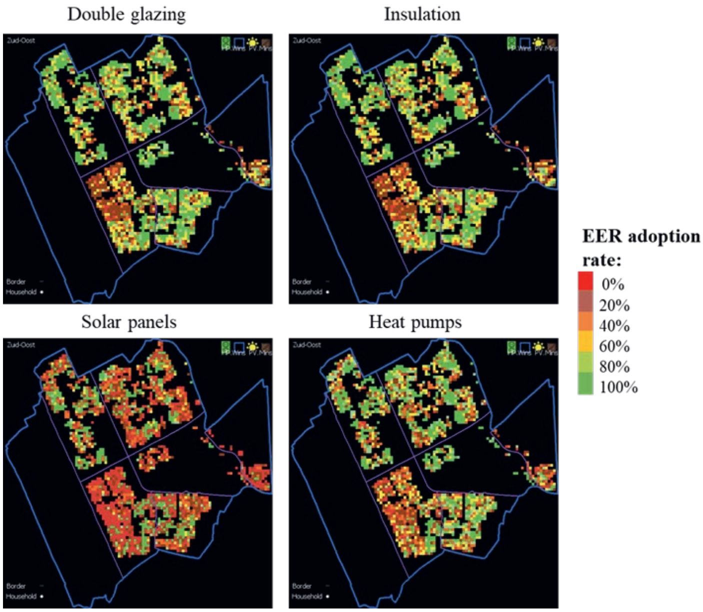


Figure 5. 4. The homeowners' adoption rate of the four EER measures in Zuidoost by 2030 based on a baseline scenario

Similarly, in the Zuid and Oost districts, double glazing and insulation of walls, roof, and floor are likely to be the most adopted measures by homeowners by 2030 (Figure 5. 5 and Figure 5. 6, respectively). These two measures have higher adoption rates in these districts than Zuidoost, varying between 60% and 100% in most areas. There are two neighborhoods in each district that lag in the adoption of these measures. In Zuid, these neighborhoods are "Buitenveldert-West" and "Buitenveldert-Oost" located in its southern part, whereas in Oost, the two neighborhoods are "Frankendael" and "Betondorp" located in the south-western part of the district.

The uptake of solar panels adoption in Zuid and Oost is also the lowest among other EER measures as in Zuidoost. However, while the PV adoption rate varies between 0-20% in Zuid, it is relatively higher in Oost, varying between 20-40%. The adoption rate of heat pumps in Zuid and Oost has a similar pattern as in Zuidoost – it is lower than it is for double glazing and insulation but higher than it is for solar panels, with the same neighborhoods of Zuid and Oost ("Buitenveldert-West" and "Buitenveldert-Oost", and "Frankendael" and "Betondorp", respectively) lagging behind.

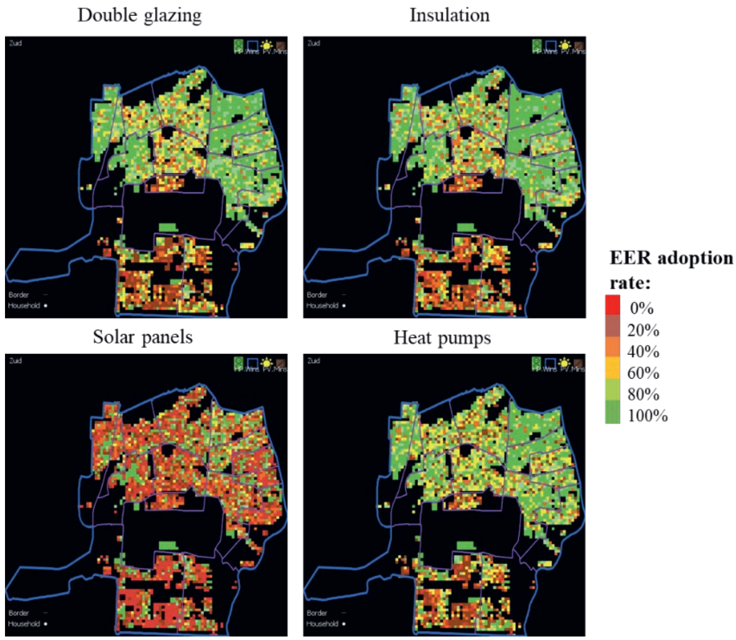


Figure 5. 5. The homeowners’ adoption rate of the four EER measures in Zuid by 2030 based on a baseline scenario

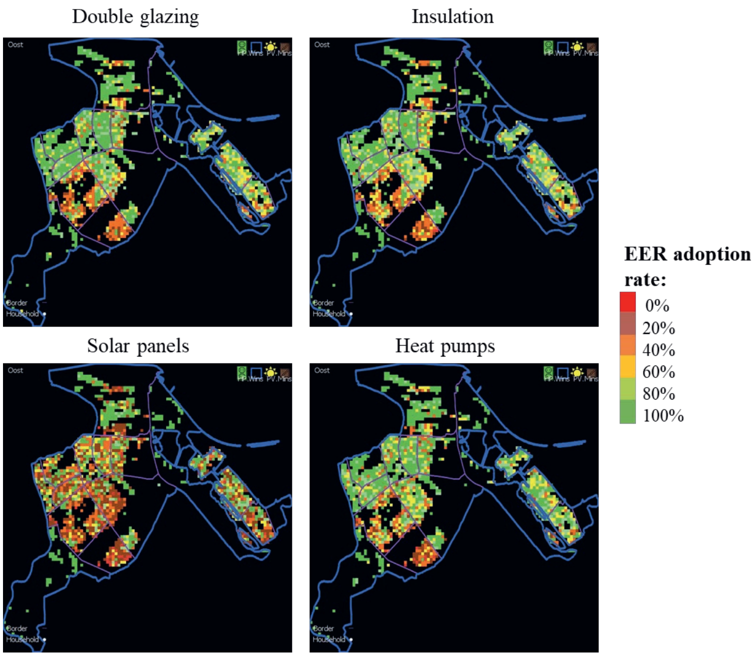


Figure 5. 6. The homeowners’ adoption rate of the four EER measures in Oost by 2030 based on a baseline scenario

Households' behavioral strategy choices

Figure 5. 7 shows the key Consumat-related parameters of homeowners in Zuidoost, including the level of need satisfaction (LNS) and uncertainty and the choice of behavioral strategies by homeowners and tenants over the simulation time collected per time step. The figure also demonstrates the cumulative number of adopted measures by households. As per the baseline scenario, tenants do not make adoption decisions; thus, we observe only choices of automated behavior strategies and no adopted measures over time except for those already in place by 2021.

The largest number of homeowners in Zuidoost choose to optimize; this trend continues throughout the simulation time, though with the highest number of choices to optimize being in time step 1 (the year 2022). We also observe sharp kinks in these plots as the data are collected per time step, and some homeowners sometimes skip a time step because their needs are satisfied. The choice of homeowners to optimize is affected by their low LNS and low uncertainty, meaning that they are unsatisfied but less uncertain.

The highest number of satisfied homeowners is observed between time steps 3 and 4 (the years 2024 and 2025, respectively), accompanied by relatively low uncertainty, which caused more homeowners to choose to repeat. At the same time, some homeowners who are satisfied with their decisions from the previous time step choose to skip. Another interesting pattern is observed during time steps between 7 and 9 (the years 2028-2030). In this simulation period, more homeowners choose to inquire, which is affected by their higher uncertainty and lower LNS.

Among the measures adopted, homeowners adopted heat pumps the most over the simulation time, even though the total number of homeowners who adopted double glazing and insulation is higher because these two measures were mostly adopted before 2021. The highest number of heat pump adopters is observed in time step 1 (the year 2022). Solar panels have a more dynamic pattern of adoption compared to double glazing and insulation; however, the PV adoption rate is still the lowest in this district.

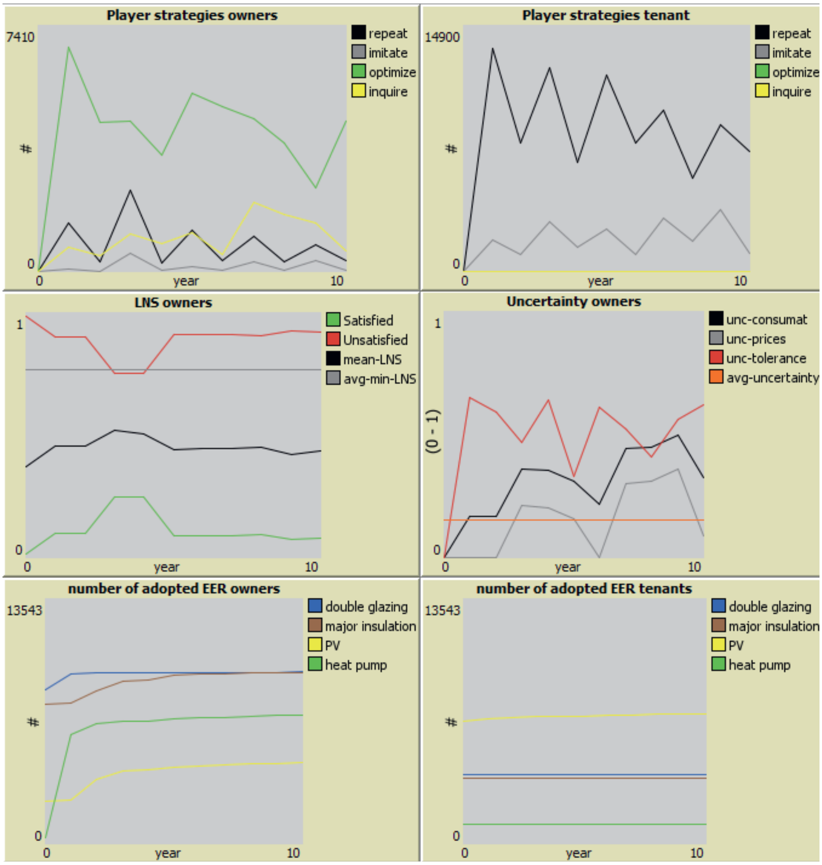


Figure 5. 7. Consumat-related parameters changing over 10 time steps in Zuidoost based on a baseline scenario

Figure 5. 8 and Figure 5. 9 show the key Consumat-related parameters of homeowners in Zuid and Oost. In Zuid, the largest number of homeowners choose to optimize with this pattern continuing throughout the simulation time (Figure 5. 8) as in Zuidoost. In Oost, the largest number of those who choose to optimize is only observed in time step 1 (the year 2022), declining over the rest of time, which is affected by the relatively higher LNS in this district as they become more satisfied through time (Figure 5. 9).

Similarly to Zuidoost, the highest number of satisfied homeowners in Zuid (Figure 5. 8) and Oost (Figure 5. 9) is observed between time steps 3 and 4 (the years 2024 and 2025, respectively). This is based on the relatively low uncertainty, which caused more homeowners to choose to repeat. An interesting pattern of homeowners' decision-making is observed in Zuid at the time step 6 (the year 2027), with the largest number of homeowners choosing to inquire. This is caused by the highest uncertainty level of homeowners during the simulation period in Zuid and their relatively low LNS.

As in Zuidoost, homeowners in Zuid and Oost also adopted heat pumps the most over the simulation time, even though the total number of homeowners who adopted double glazing and insulation is higher because these two measures were mostly adopted before 2021. The largest adoption rate of heat pumps in these two districts is observed in time step 1 (the year 2022). The PV adoption rate is still the lowest in both districts among all EER measures investigated in this study.

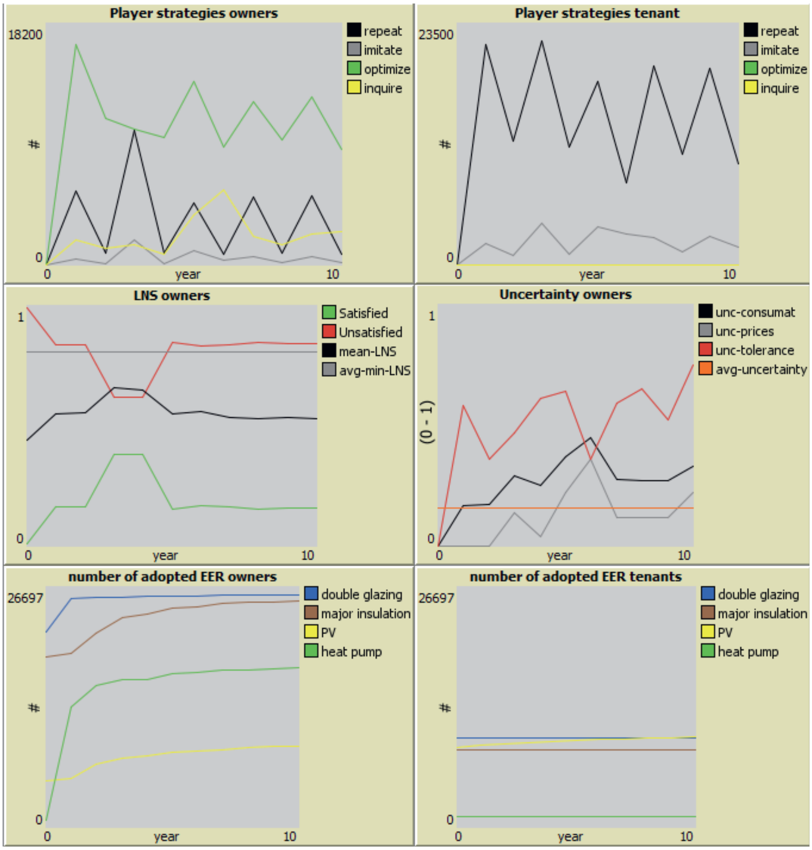


Figure 5. 8. Consumat-related parameters changing over 10 time steps in Zuid based on a baseline scenario

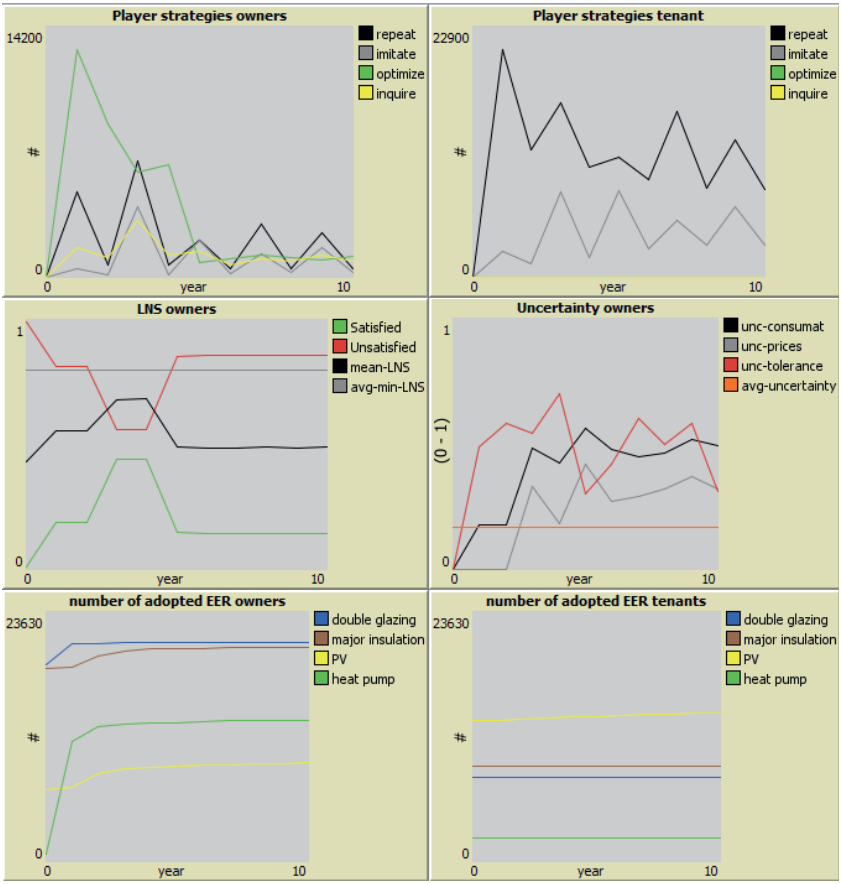


Figure 5. 9. Consumat-related parameters changing over 10 time steps in Oost based on a baseline scenario

Potential impact of the adopted EER measures on some macro variables

The model also calculates the energy consumption, energy balance, and carbon emissions affected by the adopted EER measures over the simulation period across the districts in Amsterdam. Figure 5. 10 shows these indicators calculated over time for Zuidoost. The plots on electricity and gas consumption indicate a change in homeowners' consumption in time steps 2 and 3 (the years 2023 and 2024). With increasing gas prices and moderately fluctuating electricity prices, homeowners' electricity consumption is increasing while their gas consumption is decreasing. As such, the average annual electricity and gas consumption of households in Zuidoost in 2021 was 2,211 kWh and 800 m^3, respectively (Table 5. 2). In 2030, their electricity consumption increased up to 2,810 kWh, while gas consumption reduced down to 603 m^3, on average.

The energy balance plots show that if only homeowners make adoption decisions, then the energy balance of all households is not achieved in terms of both electricity and gas by 2030. However, when the gas balance is calculated only considering homeowners, it shows a rapidly increasing dynamic over time, while the electricity balance is not achieved as the electricity consumption of homeowners is increasing. Finally, the plot on carbon emissions produced from gas and electricity consumption in Figure 5. 10 demonstrates a decreasing pattern of CO_2 emissions caused by gas consumption as the gas consumption has been diminishing over time. At the same time, the plot shows that the carbon emissions caused by increasing electricity consumption have increased insignificantly.

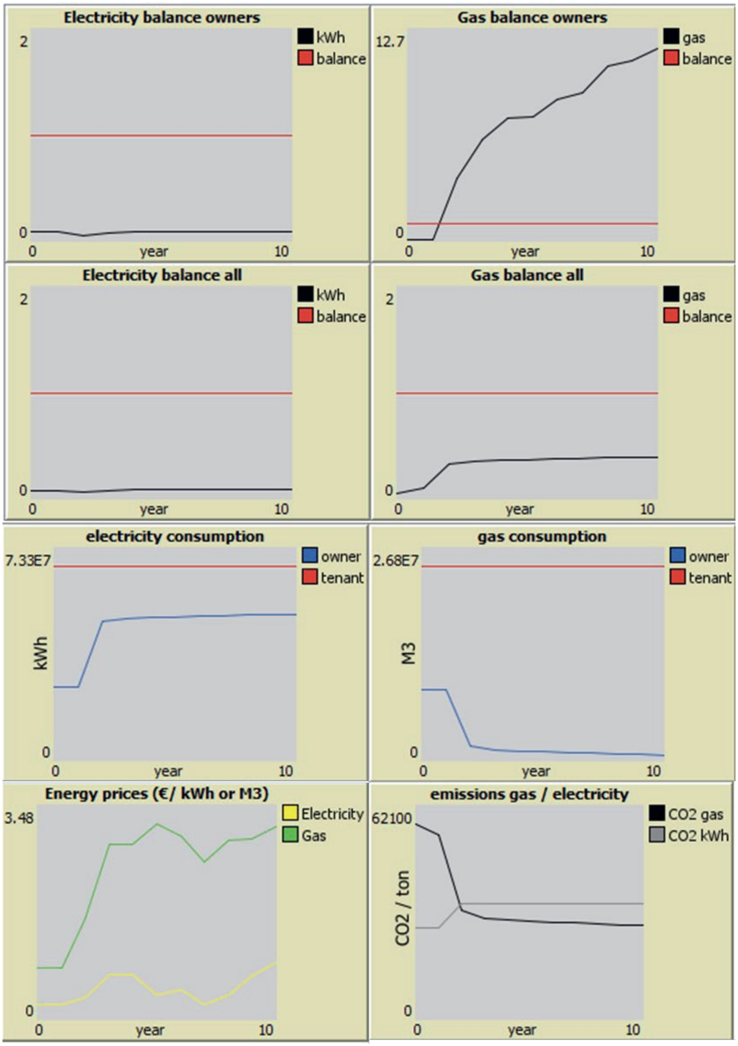


Figure 5. 10. Selected macro variables calculated for Zuidoost over 10 time steps based on a baseline scenario

Figure 5. 11 and Figure 5. 12 demonstrate the macro indicators calculated over time for Zuid and Oost, respectively. Similarly to Zuidoost, the electricity consumption has been increasing in Zuid and Oost, while the gas consumption in both districts has been declining. The largest change in these two indicators is also observed in time steps 2 and 3 (the years 2023 and 2024). The average annual electricity and gas consumption of households in 2021 was 2,166 kWh and 891 m^3 in Zuid and 2,175 kWh and 644 m^3 in Oost, respectively (Table 5. 2). In 2030 though, the average electricity consumption increased to 2,950 kWh in Zuid and 2,840 kWh in Oost, while the average gas consumption decreased to 633 m^3 in Zuid and 431 m^3 in Oost.

Interestingly, during the simulation in Zuid, the gas price shows a rapid decline starting from the time step 7 (the year 2026) (Figure 5. 11), while the gas price in Oost has a similar pattern of increasing price (Figure 5. 12) as in Zuidoost (Figure 5. 10). On the contrary, the electricity price in Zuid has a fluctuating pattern as in Zuidoost, while the electricity price in Oost has a sharp increase starting from the time step 5 (the year 2026). These price differences are caused by running the simulation separately for each district, however, in reality, the price changes should have the same pattern in all districts over time.

The energy balance plots in Zuid (Figure 5. 11) show a similar pattern as in Zuidoost (Figure 5. 10). As such, when only homeowners make adoption decisions, the energy balance of all households is not achieved in terms of both electricity and gas by 2030. The same holds in the Oost district (Figure 5. 12). Nonetheless, when the gas balance is calculated only considering homeowners, it has a rapidly increasing pattern over time, while the electricity balance is not achieved as the electricity consumption of homeowners is increasing. In contrast, the gas balance calculated only considering homeowners in Oost has a sharp increase in the time step 4 (the year 2025), followed by a sharp decline in the time step 5 (the year 2026) (Figure 5. 12).

Lastly, the plot on carbon emissions produced from gas and electricity consumption in Zuid and Oost (Figure 5. 11 and Figure 5. 12, respectively) shows a decreasing pattern of CO_2 emissions, though to a different extent as the scale of figures differs. This was caused by gas consumption as the gas consumption has been diminishing over time in both districts similar to Zuidoost. However, these plots show that the carbon emissions caused by increasing electricity consumption have increased insignificantly, which is also similar to the case of Zuidoost.

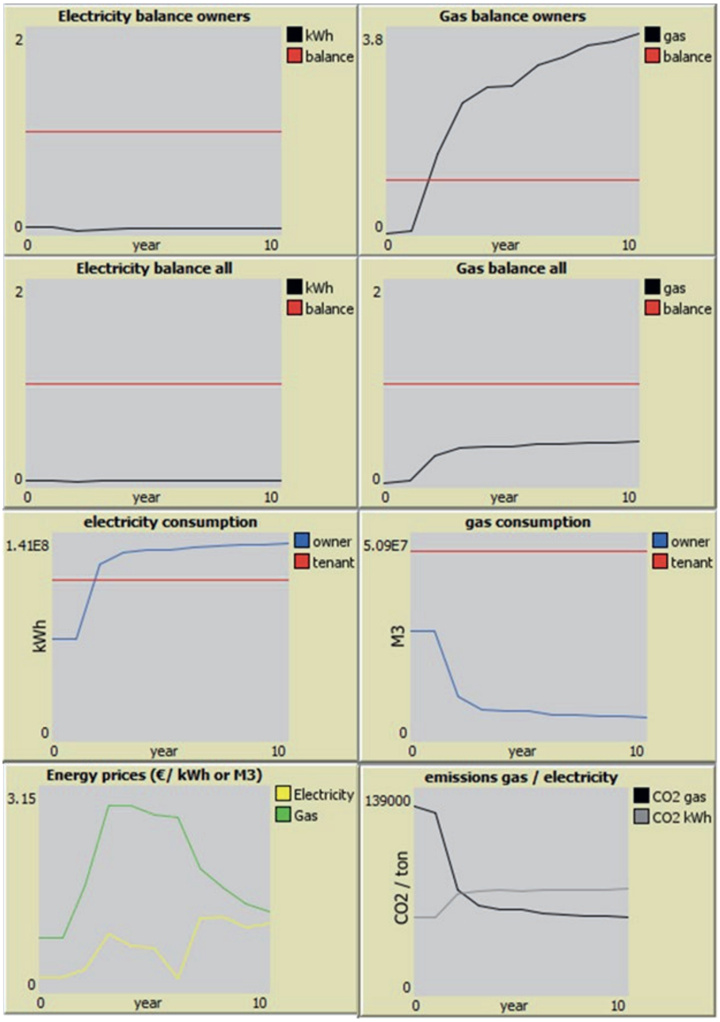


Figure 5. 11. Selected macro variables calculated for Zuid over 10 time steps based on a baseline scenario

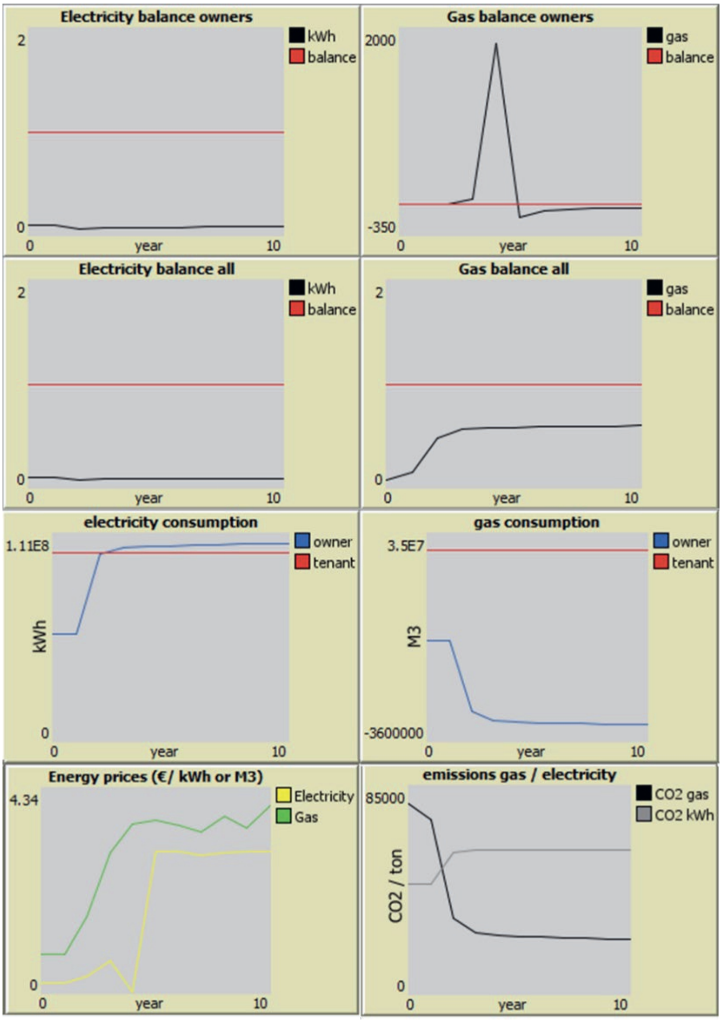


Figure 5. 12. Selected macro variables calculated for Oost over 10 time steps based on a baseline scenario

Overall, the calculation of the macro variables over time and the model output contribute to assessing to what extent the Amsterdam's CO_2 emission reduction target can be achieved by 2030. Based on the output of the baseline scenario in the seven districts of Amsterdam, the carbon emissions from electricity can drop by 11% by 2030, while the carbon emissions from gas can drop by 73.5% by 2030. In total, the combined carbon emissions from electricity and gas in the city can drop by 54% by 2030, which shows that it is possible to achieve the carbon reduction goal of Amsterdam. However, it is important to highlight that this is a rough estimation and the model has multiple limitations and does not serve the purpose of prediction. In contrast, this assessment can provide an insight of the potential impact of the elements' of the baseline scenario on achieving the climate targets while taking a PEDs pathway through increasing energy efficiency and reducing carbon emissions.

5.4.3. Model output based on alternative scenarios

The *ENERGY Pro* model has several parameters that can be varied and affect the model output. To investigate alternative scenarios, we experimented by varying two parameters – the minimal level of need satisfaction (LNS_{min}) and adoption decision-making agents *("owners-only?")*. In this subsection, our aim is to present a more general overview of the outputs, focusing on the differences across the scenarios rather than providing detailed district-level analyses as in the previous subsection. The output of the alternative scenarios for the three districts is offered in Appendices (A).

Lower LNS_{min} scenario

The first alternative scenario is based on the lower LNS_{min}. The data indicates that, on average, homeowners in Amsterdam have a threshold for the level of need satisfaction of 0.8, which is significantly high. For this reason, there are many homeowners that are unsatisfied and therefore, choose to optimize. In contrast, when we reduce the LNS_{min} to a lower level (in the current scenario, to 0.4 with a standard deviation of 0.1), the model generates a distinct output.

Across all three districts, the lower LNS_{min} caused fewer homeowners choosing to optimize and more homeowners to repeat due to an increasing level of need satisfaction as the threshold decreased (Figure A5. 1, Figure A5. 2, Figure A5. 3). This, in turn, led to a change in the EER adoption rates. The key change in the model output relates to the uptake of solar panels and heat pumps. Notably, we found that the adoption rate of heat pumps is increasing slower than that of solar panels, in contrast to the adoption rates observed in the baseline scenario (Figure A5. 1, Figure A5. 2, Figure A5. 3). With the change in LNS_{min} and consecutively a lower heat pump uptake, the gas consumption of homeowners is much higher, while their electricity consumption is substantially lower than it was in the baseline scenario (Figure A5. 4, Figure A5. 5, Figure A5. 6). These changes also affected carbon emissions. That is, carbon emissions from electricity in all three districts have decreased, while with the adoption of fewer heat pumps, the emissions from gas have decreased significantly less than in the baseline scenario (Figure A5. 4, Figure A5. 5, Figure A5. 6).

Overall, based on the output of this alternative scenario with a change in LNS_{min} in the seven districts of Amsterdam, the carbon emissions from electricity can drop by 26.4% by 2030, while the carbon emissions from gas can drop by 45.2% by 2030. Under this scenario, the combined estimated carbon emissions from electricity and gas in the city are projected to decrease by 39.3% by 2030. This still falls short of Amsterdam's carbon reduction goal, indicating that unlike in the baseline scenario, additional measures may be needed to achieve the desired outcome.

Tenants inclusion scenario

Another alternative scenario is expanding the list of adoption decision-making agents to tenants. In Amsterdam, tenants form a substantial part of households across its districts, constituting 75.6% in Zuidoost, 66.5% in Zuid, and 69.8% in Oost (Table 5. 2). The prevalence of tenants is further underscored by the fact that most of these households reside in apartment dwellings (approximately 70-80%), which in turn comprise a significant 70-80% of the residential built environment in the city (Table 5. 2). For these reasons, tenants can make a big difference in urban energy transition if included in the EER adoption decision-making.

As such, across all three districts, tenants being included in the adoption decision-making increased the number of households choosing to optimize and inquire, which in turn positively affected the uptake of the EER measures (Figure A5. 7, Figure A5. 8, Figure A5. 9). The largest uptake among the EER measures concerns the adoption of double glazing followed by insulation across all three districts. In contrast, while the adoption of solar panels and heat pumps has also increased, their adoption rate differs across the districts (Figure A5. 7, Figure A5. 8, Figure A5. 9). With the inclusion of tenants to adoption decision-making, their electricity consumption increases and gas consumption decreases, similar to the baseline scenario with owner-occupied households (Figure A5. 10, Figure A5. 11, Figure A5. 12). These changes significantly affect the overall gas balance contributing to an extensive heat surplus and a substantial reduction of carbon emissions from gas (Figure A5. 10, Figure A5. 11, Figure A5. 12).

Overall, based on the output of this alternative scenario with tenants in the seven districts of Amsterdam, the carbon emissions from electricity can increase by 15% by 2030, while the carbon emissions from gas can drop by 100% by 2030 meaning zero-gas-emissions. Under this scenario, the combined estimated carbon emissions from electricity and gas in the city are projected to decrease by 74.6% by 2030. This shows that it is possible to achieve Amsterdam's carbon reduction goal and significantly overperform it.

5.5. Discussion, limitations, and future research

5.5.1. Discussion of the main output

This subsection discusses valuable insights obtained from the *ENERGY Pro* model, including the potential adoption rate of the four EER measures across different districts in Amsterdam by 2030. The model outputs also provide an understanding of households' behavioral strategy choices over the simulation period and the potential impact of the adopted EER measures on energy consumption, energy balance, and carbon emissions. In addition, we also address the sensitivity analysis results.

Differences in potential EER adoption rate across the scenarios

Among EER measures, double glazing and insulation of roof, floor, and walls are the most adopted measures under all three examined scenarios, while solar panels and heat pumps adoption rates vary across the scenarios and the districts. The higher adoption rates of double glazing and insulation can be primarily attributed to their early adoption, which occurred prior to 2021. This can be attributed to the implementation of the Building Code, which mandated a minimum heat-insulation requirement for all construction components starting from 1992 [120]. Across the districts, double glazing and insulation have been adopted more in Zuid and Oost compared to Zuidoost including older dwellings built before 1992. This might also be related to the higher socio-economic status of homeowners in those two districts. More homeowners in these two districts are highly educated, have upper-middle or high income, and more homeowners are in the working age group (between 35-64). This result supports previous research suggesting the importance of building features such as construction year and socio-demographic characteristics falling into the categories mentioned above in influencing the EER adoption rates in the Netherlands [76].

In the baseline scenario, the least adopted measure is solar panels in all three districts, with even lower PV adoption rate in Zuidoost and Zuid. In these two districts, there are more homeowners without children and with older houses. While households without children might be less motivated to adopt solar panels and reduce energy expenditures, households living in older/historical dwellings might have physical constraints for PV installation. This finding is also in line with the insights from an earlier study on decision-making processes of the energy efficiency renovations of Dutch homeowners [94]. In terms of heat pumps, the adoption rate is higher than that of PV but lower than that of double glazing and insulation across all districts under the baseline scenario.

In the lower LNS_{min} scenario, the adoption rate of heat pumps is increasing slower than that of solar panels, in contrast to the adoption rates observed in the baseline scenario. This might be attributed to a higher level of need satisfaction of homeowners. Finally, in the tenants scenario, while the adoption of both solar panels and heat pumps have increased, their adoption rate differs across the districts. The differences in adoption of these measures might be related to tenants' heterogeneity in their socio-demographic and dwelling characteristics across the districts.

Overall, in all three scenarios, the EER adoption rates vary across all districts in Amsterdam. It is clear that the context of each area matters for achieving PEDs and taking it into account in developing PEDs pathways is important. Moreover, two neighborhoods in each presented district lag behind in adopting all EER measures, confirming their specific context's impact on EER adoption. Understanding these neighborhoods' unique challenges and opportunities can provide valuable insights about certain factors significantly influencing households' adoption behavior. This insight also supports recent research findings on neighborhood determinants playing a significant role in EER adoption (e.g., PV) in the Netherlands [192]. Therefore, as a follow-up study, it will be beneficial to further conduct neighborhood-scale analysis that could help us develop more accurate and tailored pathways for achieving energy efficiency goals.

Differences in households' behavioral strategy choices across the scenarios

Under the baseline scenario, homeowners across the three selected districts mostly chose to optimize, which is caused by their low LNS and low uncertainty. While most of homeowners optimized, the pattern of choosing to optimize differs across the districts with the lower number of optimizing homeowners in the second half of the simulation observed in Oost. This pattern was caused by higher LNS of homeowners in this district. The second most chosen strategy by homeowners under the baseline scenario in all three districts is to inquire. The trend of a growing number of homeowners opting to inquire becomes evident in the later time steps of the simulation, coinciding with uncertainty increasing over time.

In contrast to the baseline scenario, fewer homeowners chose to optimize and more homeowners to repeat in the lower LNS_{min} scenario. This was caused by their increasing level of need satisfaction, which led to a change in the uptake of the EER measures. On the other hand, similarly to the baseline scenario, a greater proportion of households chose to optimize and inquire in the tenants scenario. The sole alteration in this scenario was the inclusion of tenants in adoption decision-making. This change has led to a higher uptake of the EER measures with adoption rates varying across the districts.

Differences in potential impact of the EER uptake on carbon emissions across the scenarios

The calculation of the macro variables based on the model output across the three scenarios provides an insight to what extent the Amsterdam's climate target can be achieved by 2030. Under the baseline scenario, total carbon emissions from electricity and gas across all seven city districts can decrease by 54% by 2030, with the major contribution coming from a significant reduction in gas consumption. This aligns with Amsterdam's target of reducing carbon emissions by 55% by 2030. However, the energy balance of all households in terms of both electricity and gas, which is key for PEDs, is not projected to be achieved when adoption decisions are solely made by homeowners.

In contrast, under the lower LNS_{min} scenario, the combined estimated carbon emissions from electricity and gas in the city are projected to decrease by 39.3% by 2030, which falls short of the city target. This is predominantly caused by the increasing gas consumption under this scenario. The outcome of this scenario indicates that additional measures will be essential to achieve the climate target of the city. In the contrary, under the tenants scenario, total carbon emissions from electricity and gas in the city are projected to decrease by 74.6% by 2030, which substantially overachieves the 2030 city target. This estimation is mainly caused by the significant gas consumption reduction by all households resulting from an extensive heat surplus. The outcome of the tenants scenario demonstrates that the energy transition can be accelerated if tenants are also included in EER adoption decision-making. According to the Dutch housing stock in 2022, tenants constitute 71% of residents in Amsterdam [193], however, yet with little opportunity to participate in the energy transition. Including tenants in EER adoption decision-making can not only enhance the energy transition in Amsterdam, but also guarantee an inclusive and equitable process [194].

Overall, even though these estimations are provisional and not forecasted, they provide a valuable understanding of the potential of achieving the carbon emission target.

Sensitivity analysis results

The sensitivity analysis of the model output was conducted in our method article [164] following the one-factor-at-a-time approach. The key findings derived from the sensitivity analysis highlight several factors that positively influence the EER adoption rate of homeowners. First, homeowners with lower uncertainty regarding energy prices have a higher EER adoption rate as they tend to optimize. This indicates the importance of reducing households' uncertainty to encourage them to adopt more EER measures. Second, connections with highly similar neighbors, based on their location of residence, age, income, and education, significantly contributes to an increased adoption rate of EER among homeowners. The influence of more similar neighbors on EER decisions of homeowners become more pronounced, emphasizing the significance of such social connections in driving adoption behavior in a neighborhood. This result also confirms recent research findings on positive spatial effects on EER adoption in the Netherlands suggesting that social interactions in a neighborhood enhance green behavioral imitations [192]. This point is also evident from previous research on PV diffusion, which indicates that people tend to imitate green behaviors to conform to social norms and maintain group identity [195]. Third, higher energy prices also contribute to a higher rate of EER adoption as homeowners get more motivated to reduce their energy expenditures by saving energy through adopting such measures. Additionally, the sensitivity analysis, performed following the alteration of two parameters, reveals a greater uptake of the EER measures in response to higher gas prices compared to higher electricity prices. This finding highlights the potential effectiveness of raising gas prices as a means to accelerate EER adoption.

5.5.2. Limitations and future research

The major limitation of this study is the insufficient availability of data. Due to the lack of data, this study employs a proxy variable to represent one of the key variables in the model, LNS_{min} [164], which does not fully reflect reality. Furthermore, due to the data limitations, this research focuses primarily on homeowners, inadvertently overlooking the significant role played by landlords in the energy transition. Landlords, who make EER adoption decisions on behalf of tenants, are also key stakeholders in this process. Future research, with access to comprehensive data, could address this issue by investigating landlord behavior and decision-making. This could involve examining aspects such as the allocation of incentives from energy savings, responsibility for energy bills and taxes, and other related factors. By delving into these dynamics, a more comprehensive understanding of the energy transition can be attained. Moreover, the limited availability of data constrained the validation of the model solely to expert validation, while the calibration process was not feasible. The inclusion of real-time data on adopted EER measures would have facilitated, to some extent, the calibration of the model. Unfortunately, the absence of such real-time data hindered this important step in refining the model's accuracy.

Another limitation of this study is the partial representation of the energy system within the model with the focus on households only. While it is inherent to the nature of this research, aiming to deepen our understanding of household decision-making, it is crucial to recognize the importance of incorporating other elements of PEDs and the wider energy transition. These elements include urban mobility, system flexibility, and involvement of various stakeholders in the energy system. Urban mobility, for instance, can serve as energy storage and contribute to achieving climate targets, while system flexibility is crucial for establishing dynamic and virtual PEDs alongside autonomous ones [29]. Furthermore, besides households, the implementation of these PEDs processes involves participation from and not limited to government bodies, energy companies, and housing corporations [135]. Ideally, these elements should be modeled as submodels and integrated into a more comprehensive energy model. However, it is important to acknowledge the existing limitations in terms of data availability and technical feasibility when implementing such complex models.

Another limitation of this study is the limited number of time steps. A coarse time granularity hindered capturing the emergent behavior of households. Additionally, this limitation prevented us from utilizing standardized linear regression for the sensitivity analysis. The number of time steps limited to 10 did not provide sufficient output to examine the interaction of multiple variables within the regression framework. While we chose a one-year time step, as it is widely accepted for calculating the energy balance of PEDs [135], future research could benefit from using more granular time steps. This approach could shed light on the emergent behavior of households and address the limitation of conducting regression analysis.

Finally, this study's design falls short in addressing socio-psychological aspects due to data limitations, making it challenging to establish causality in household decision-making. Additionally, the agents in the Consumat framework are not culture-aware which hinders the comprehensiveness of the findings. Considering the cultural aspect would enhance the analysis of household behavior across different city districts with diverse population contexts. Therefore, incorporating socio-psychological and cultural aspects can help understand "why" households make certain decisions, in addition to already explored "how". This interdisciplinary approach can be valuable not only in the development of energy transition models but also in future studies at larger scales, such as inter-city or inter-country analyses. It also allows for a more holistic examination of the factors influencing human behavior and decision-making, leading to a deeper understanding of complex phenomena like PEDs.

5.6. Conclusion and policy recommendations

This study explores how homeowners in Amsterdam make EER adoption decisions and how these decisions differ across the city districts using the combination of social simulation and spatial microsimulation. We developed a spatially-explicit empirically-driven model *ENERGY Pro* to investigate human-centric PEDs pathways. Additionally, the model examines to what extent households in Amsterdam can contribute to the city's CO_2 emission reduction target by achieving PEDs via energy consumption reduction, energy efficiency, and renewable energy generation.

Our findings reveal that EER adoption rates vary across districts in Amsterdam due to household heterogeneity and their socio-demographic and dwelling characteristics. Therefore, it is important to consider the local context when developing PEDs. We also found that similar neighbors' EER decisions influence homeowners, underscoring the role of social connections in adoption behavior. Another key finding, based on sensitivity analysis, highlights that higher energy prices, particularly gas prices, motivate homeowners to adopt EER measures, as also evident from increased uptake since the 2022 energy crisis [196]. Furthermore, the outcome of the tenants scenario demonstrates that including tenants in decision-making can significantly accelerate the energy transition and help achieve carbon emissions reduction goals.

Based on these key findings, we offer a list of policy recommendations that could be useful for policymakers in Amsterdam and in similar cities for effective PEDs development:

- *Introducing area- or context-based policy interventions* considering challenges and opportunities of each area (i.e., neighborhood) as well as heterogeneous characteristics of the population.
- *Including tenants in EER adoption decision-making* to achieve the energy balance and carbon emissions reduction goal with governmental support in terms of information and, if necessary, financial means as they are important drivers in the energy transition.
- *Fostering neighborhood cohesion* by promoting collaboration and cooperation among neighbors and supporting local initiatives, which in turn can also contribute to the local energy transition.
- *Increasing gas taxes* along with increasing public awareness, technological advancement, and access to financial resources to ensure just and inclusive energy transition. In turn, collected gas taxes could be used for EER subsidies to support those who cannot afford it.

Overall, these policy implications developed based on the model output can serve as a useful addition to the current policy schemes on urban energy transition in Amsterdam as they offer area-based interventions for the local transition.

This study makes a set of unique contributions to the literature as it is at the cutting edge of socio-economic energy systems research and stands out for its engineering importance and significant societal impact. It creates a discussion of and offers possible solutions for urgent global concerns such as climate change and the energy crisis. We summarize these contributions as follows:

1. This study offers an example of spatially explicit empirically-driven energy models that are still scarce and demonstrates the research possibilities of such models. As such, our study contributes to the literature by developing such an extensive model that focuses on four EER measures as most of the earlier energy models have rarely explored the adoption of multiple (complementary) technologies [167].
2. The combination of agent-based modeling (ABM) and spatial microsimulation provides a deeper and more meaningful explorative analysis of the urban energy transition in Amsterdam by 2030, which is the first study of its kind. As the generated synthetic population of Amsterdam substantially extends the dataset, it sheds light on more extensive information and helps thoroughly analyze the city districts, and can be used for other studies on Amsterdam's households.
3. This study unpacks both top-down and bottom-up causations of emergent behavior of the energy system. The top-down causation was depicted by the impact of changes in macro variables such as e.g. energy prices (macro-level cause) on households' decision-making. On the other hand, the bottom-up causation was represented by the effect of changes in households' individual characteristics on changes in their decision-making (micro-level event) and its consequences for the energy transition (macro-level effect) and for other households (micro-level effect).
4. Our study adds sociality to building the model following the Consumat conceptual model to capture social interactions between similar neighbors and understand how these interactions can contribute to developing PEDs.

To conclude, this study offers a human-centric approach to the energy transition highlighting the necessity for reducing energy consumption and adopting technologies for clean energy production, which contributes to preserving the environment and saving financial means for energy.

Appendices

A. The output of the alternative scenarios for the three districts

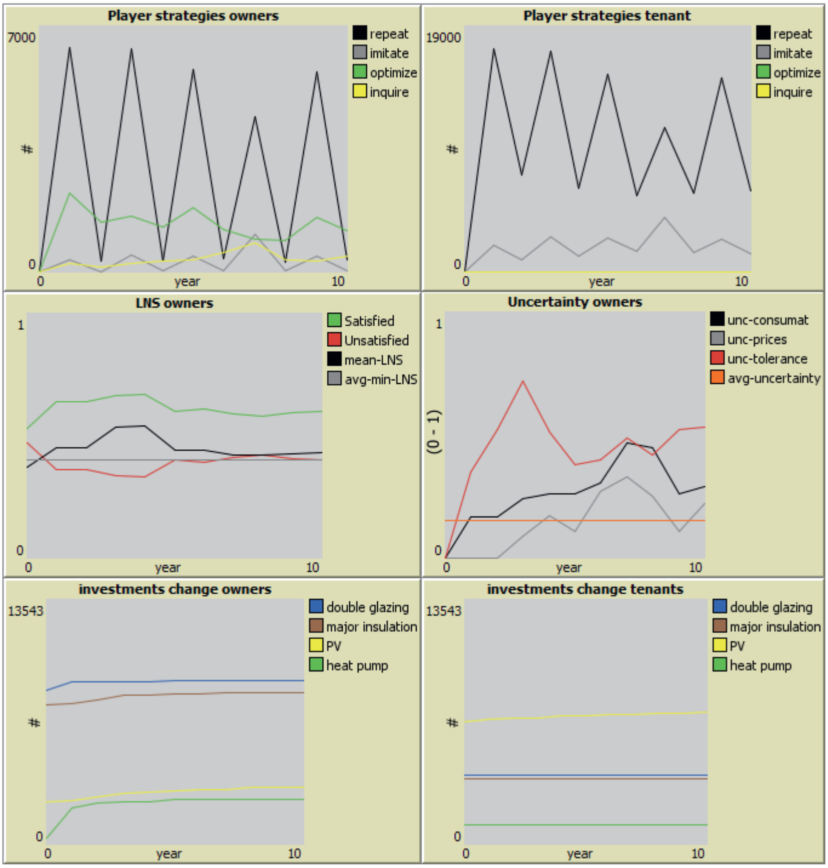


Figure A5. 1. Consumat-related parameters changing over 10 time steps in Zuidoost based on an alternative scenario (lower LNS_{min})

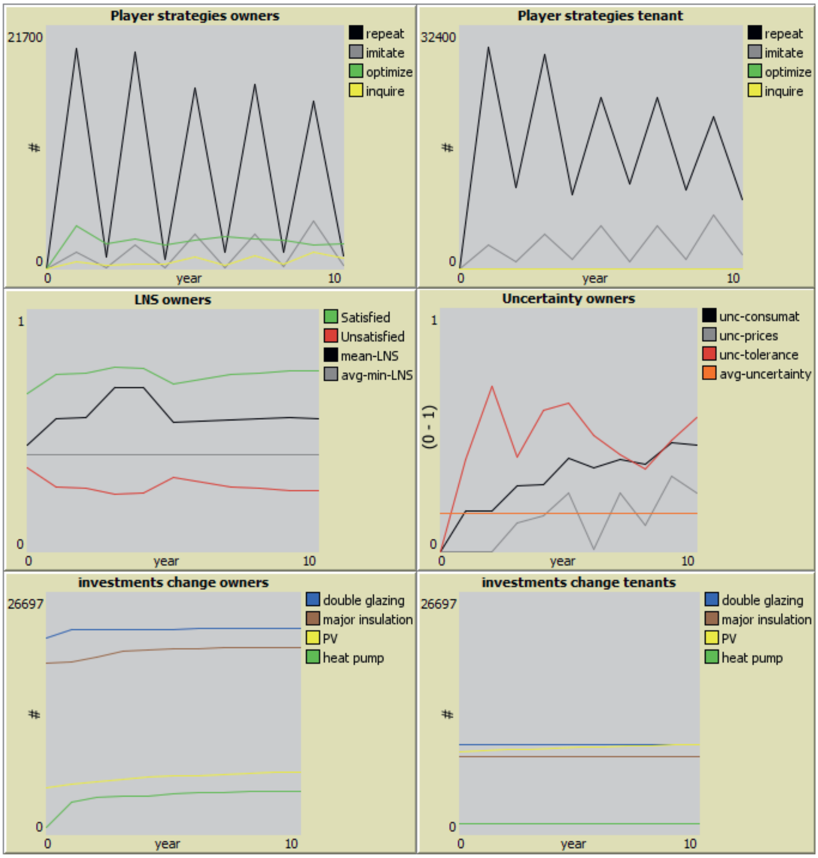


Figure A5. 2. Consumat-related parameters changing over 10 time steps in Zuid based on an alternative scenario (lower LNS_{min})

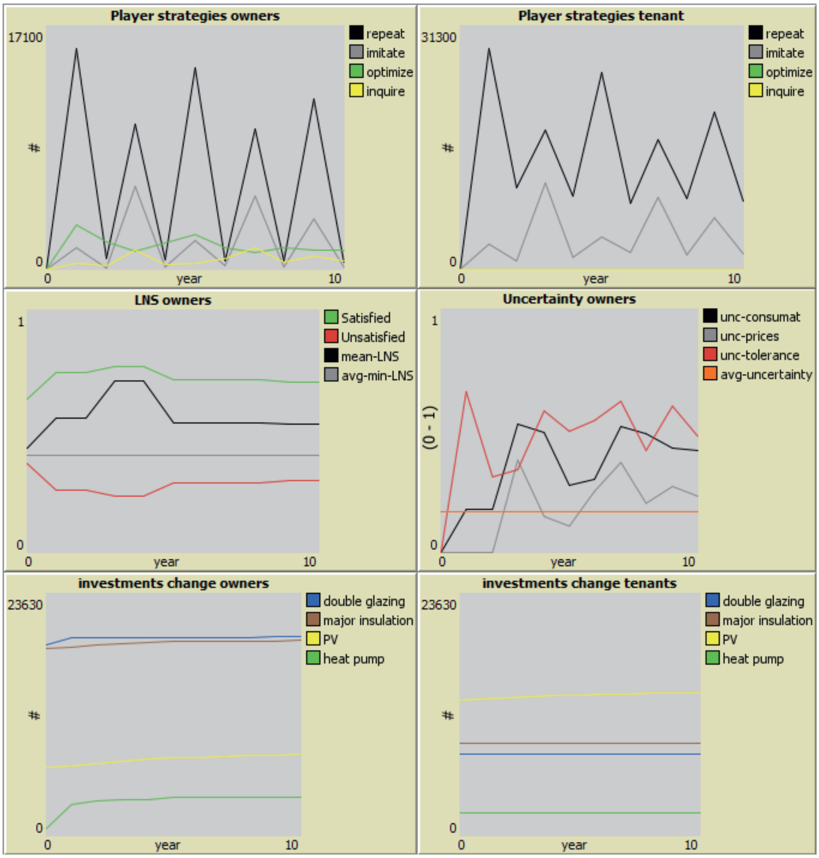


Figure A5. 3. Consumat-related parameters changing over 10 time steps in Oost based on an alternative scenario (lower LNS_{min})

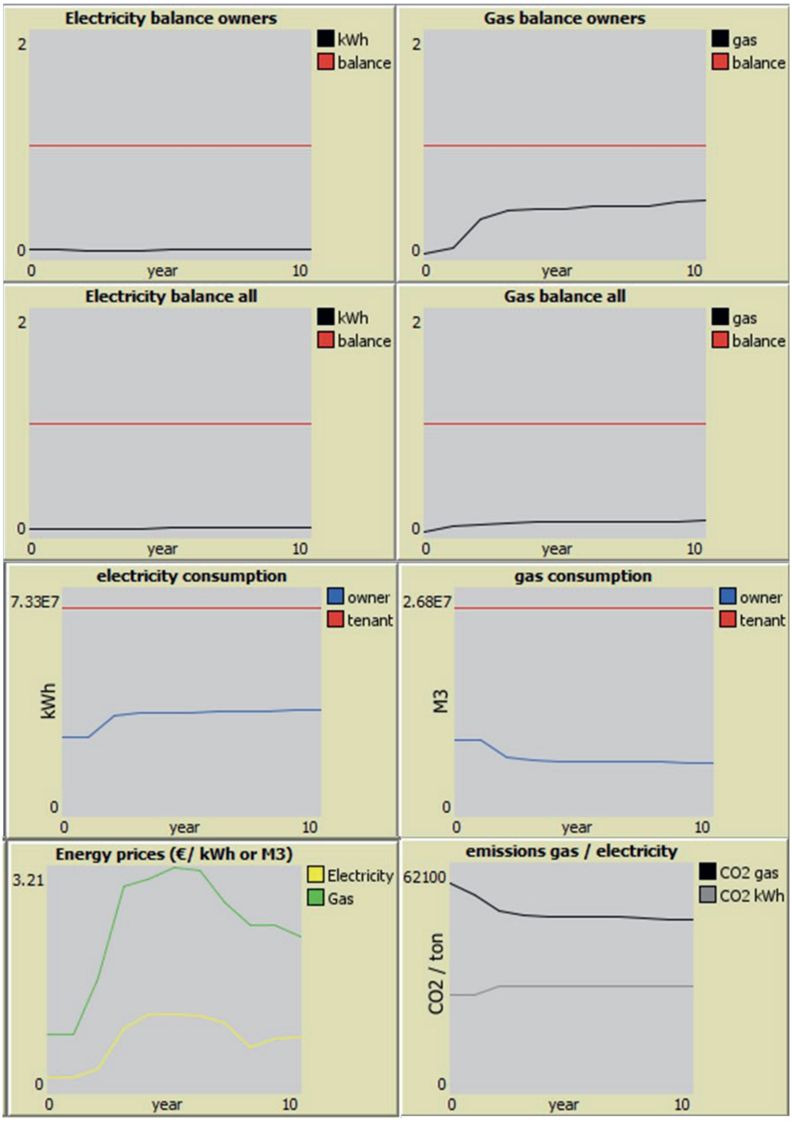


Figure A5. 4. Selected macro variables calculated for Zuidoost over 10 time steps based on an alternative scenario (lower LNS_{min})

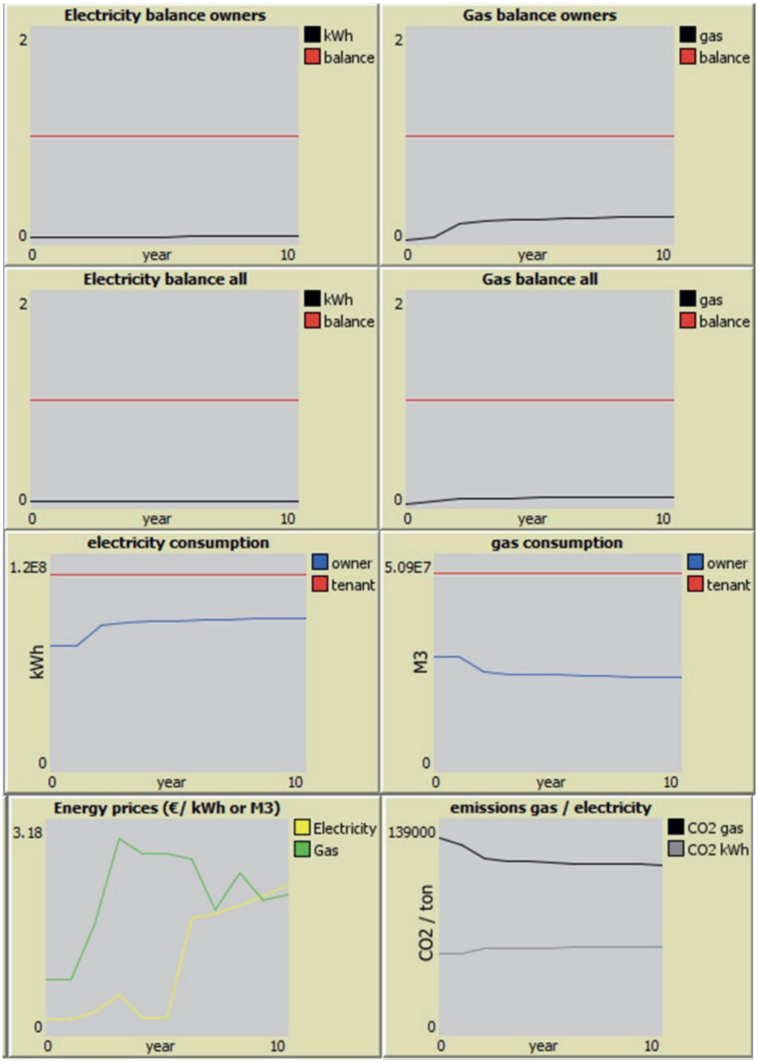


Figure A5. 5. Selected macro variables calculated for Zuid over 10 time steps based on an alternative scenario (lower LNS_{min})

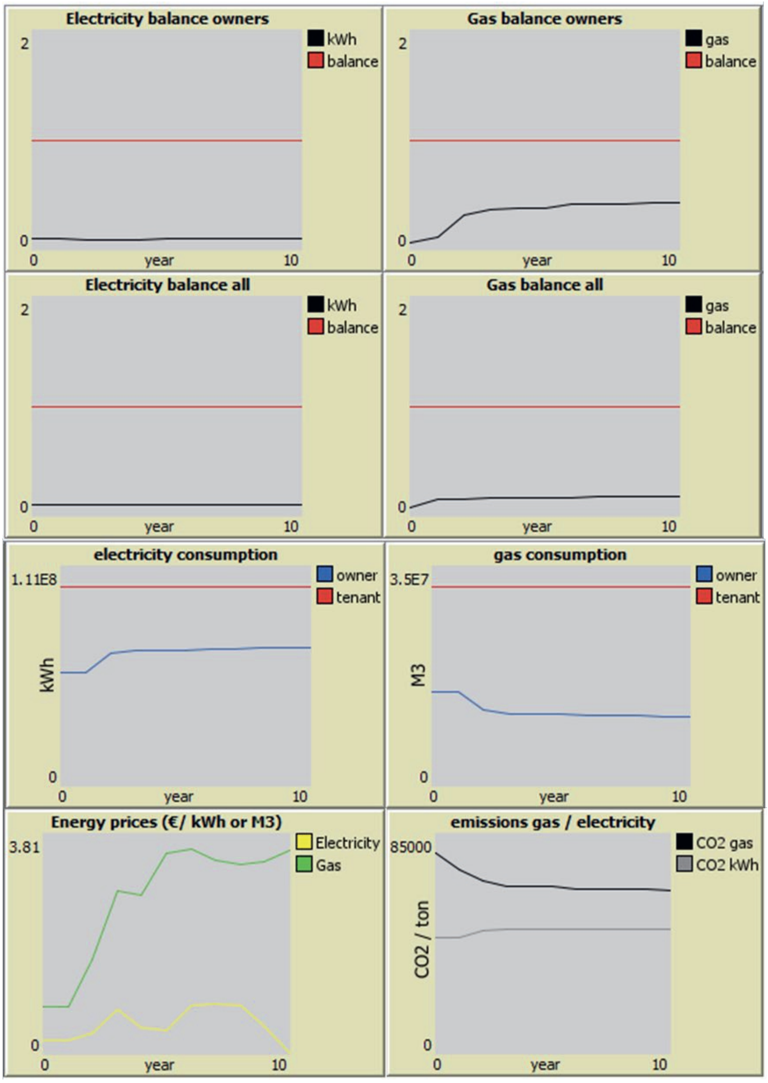


Figure A5. 6. Selected macro variables calculated for Oost over 10 time steps based on an alternative scenario (lower LNS_{min})

Chapter 5

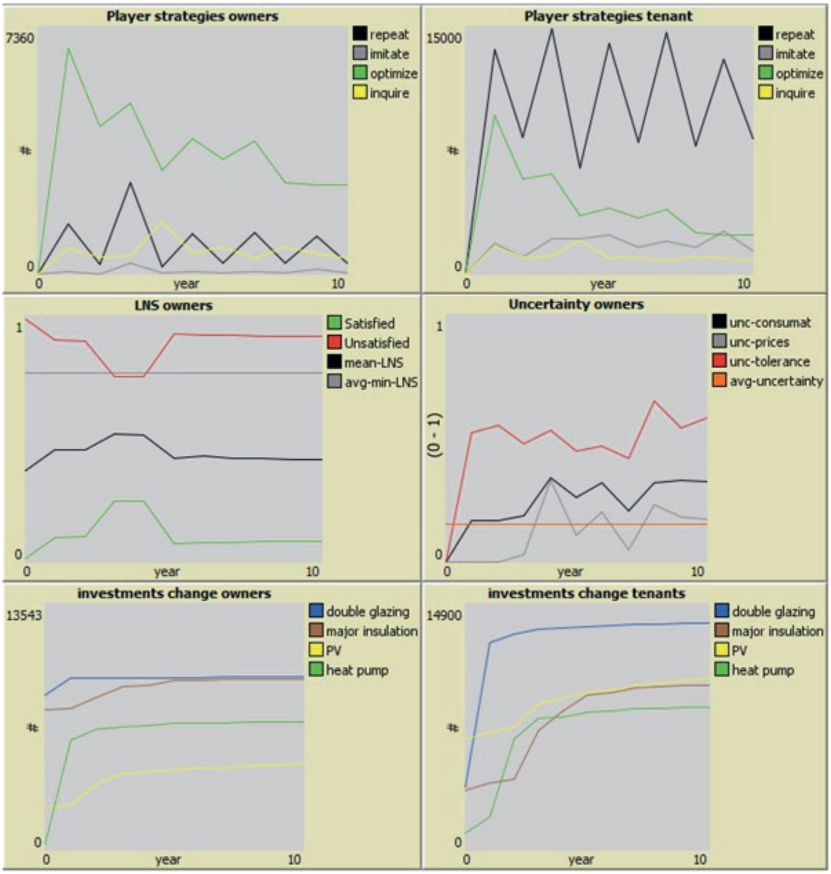


Figure A5. 7. Consumat-related parameters changing over 10 time steps in Zuidoost based on an alternative scenario (tenants)

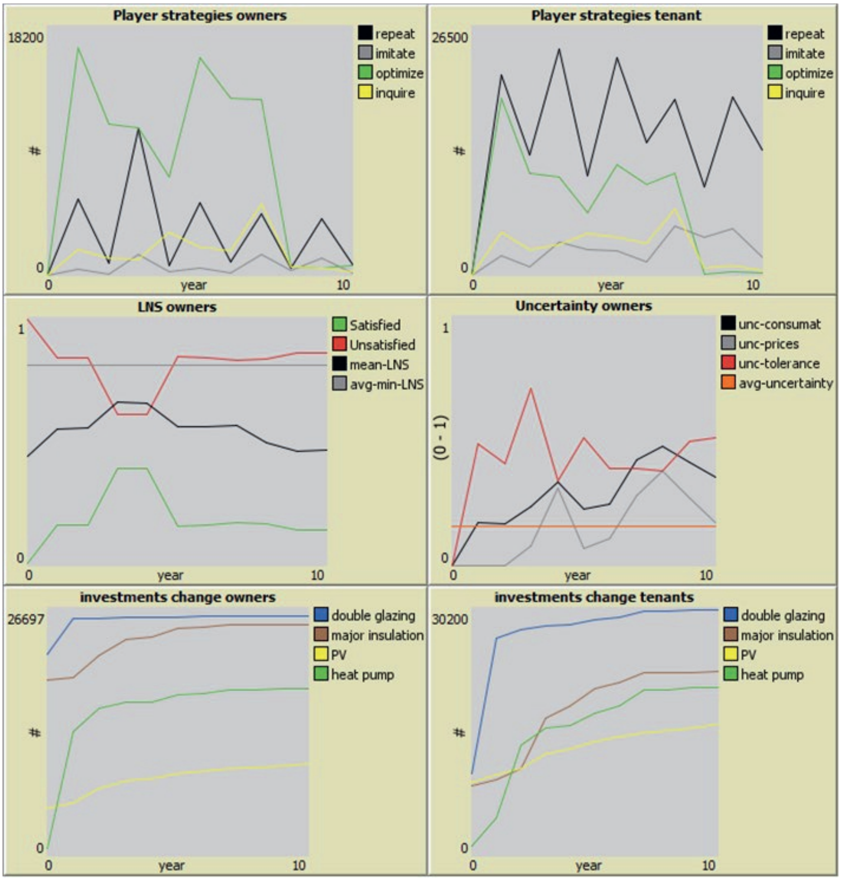


Figure A5. 8. Consumat-related parameters changing over 10 time steps in Zuid based on an alternative scenario (tenants)

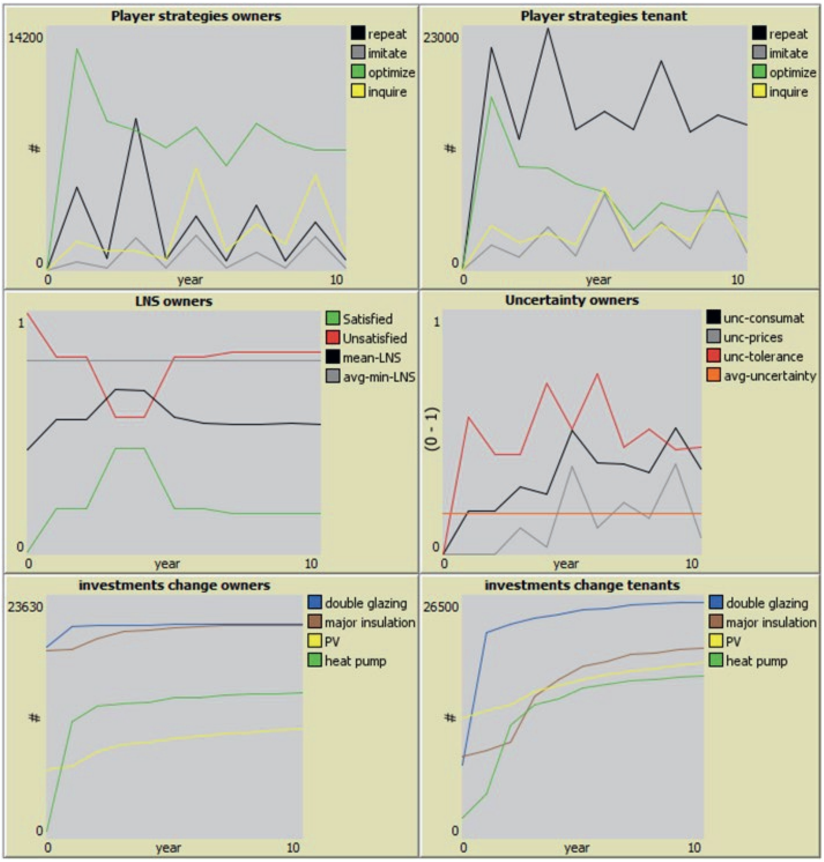


Figure A5. 9. Consumat-related parameters changing over 10 time steps in Oost based on an alternative scenario (tenants)

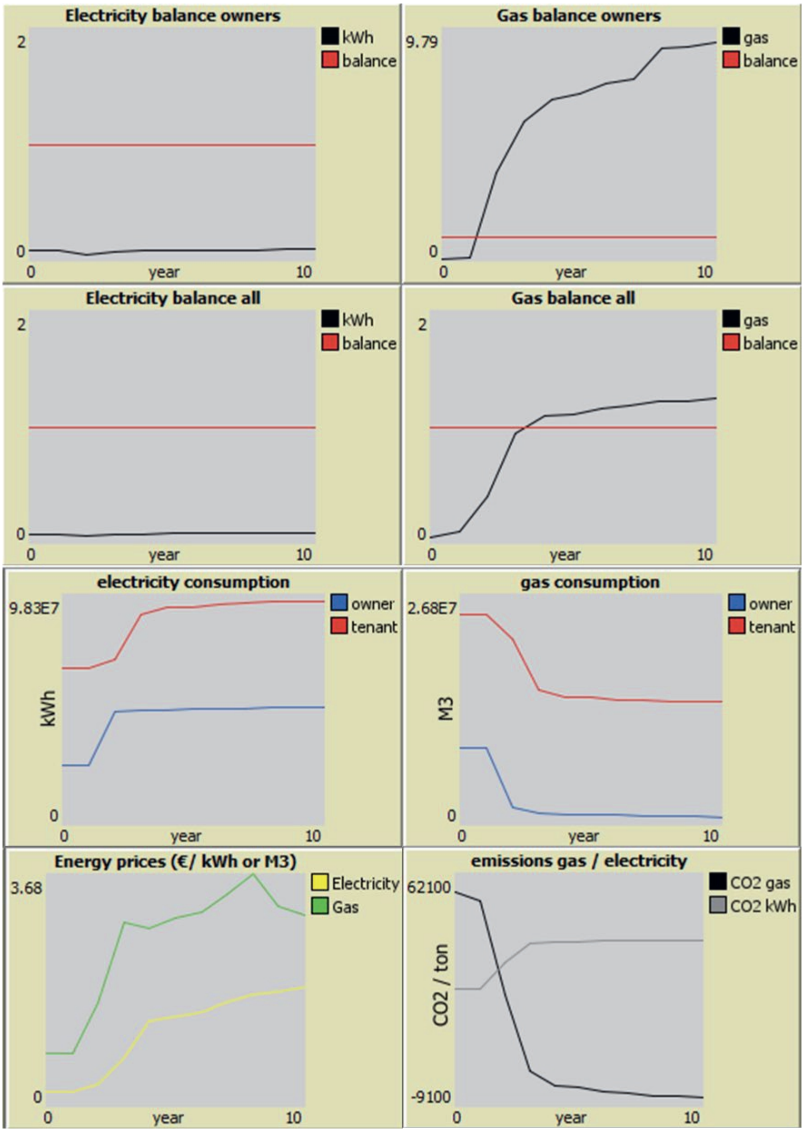


Figure A5. 10. Selected macro variables calculated for Zuidoost over 10 time steps based on an alternative scenario (tenants)

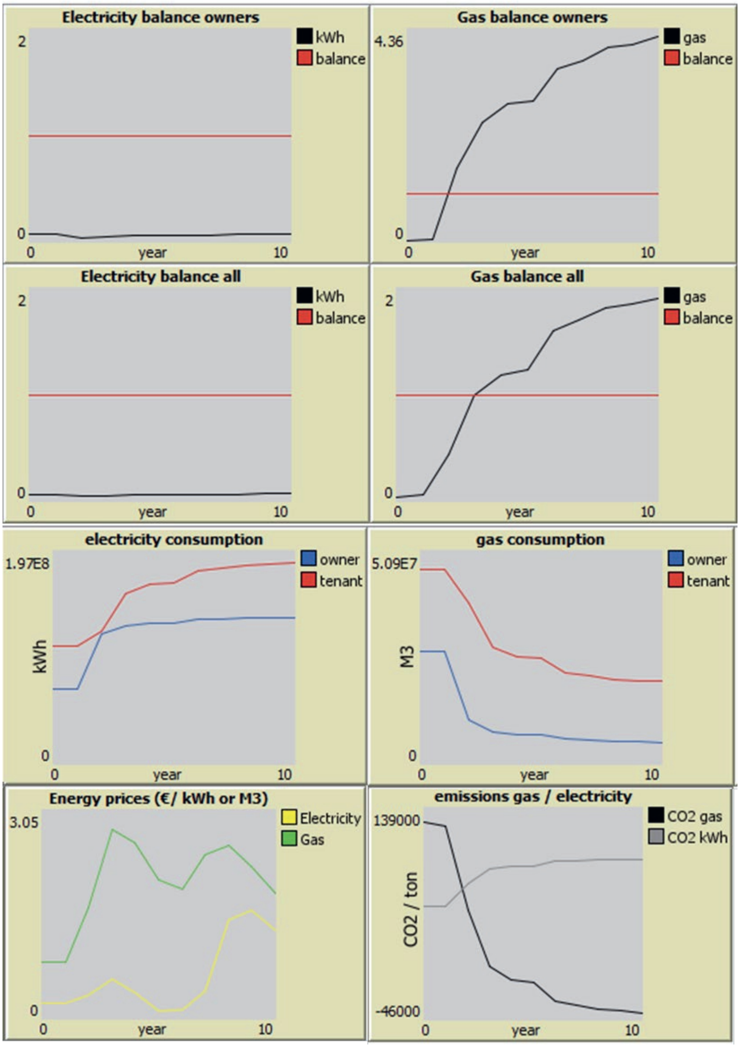


Figure A5. 11. Selected macro variables calculated for Zuid over 10 time steps based on an alternative scenario (tenants)

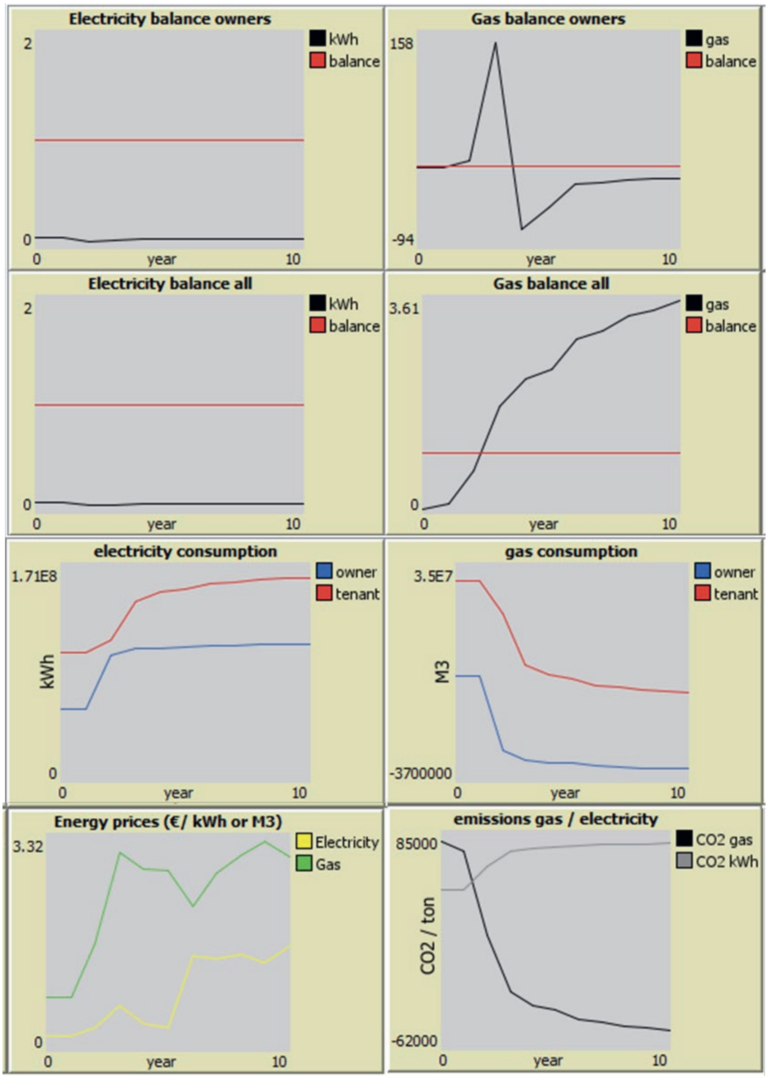


Figure A5. 12. Selected macro variables calculated for Oost over 10 time steps based on an alternative scenario (tenants)

B. The output of the baseline scenario for the rest of the districts

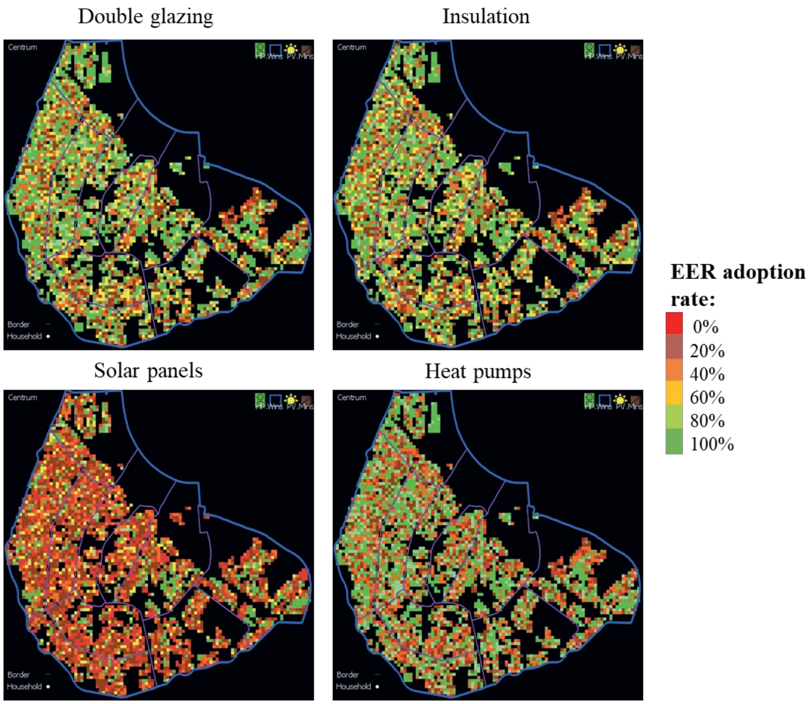


Figure B5. 1. The homeowners' adoption rate of the four EER measures in Centrum by 2030 based on a baseline scenario

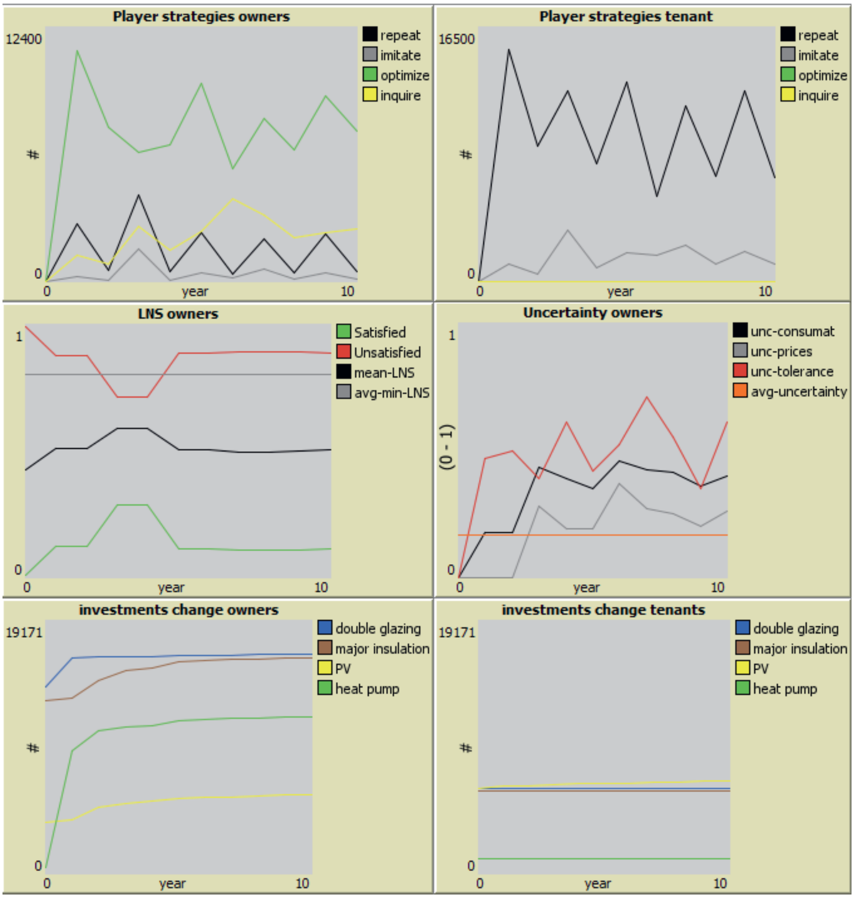


Figure B5. 2. Consumat-related parameters changing over 10 time steps in Centrum based on a baseline scenario

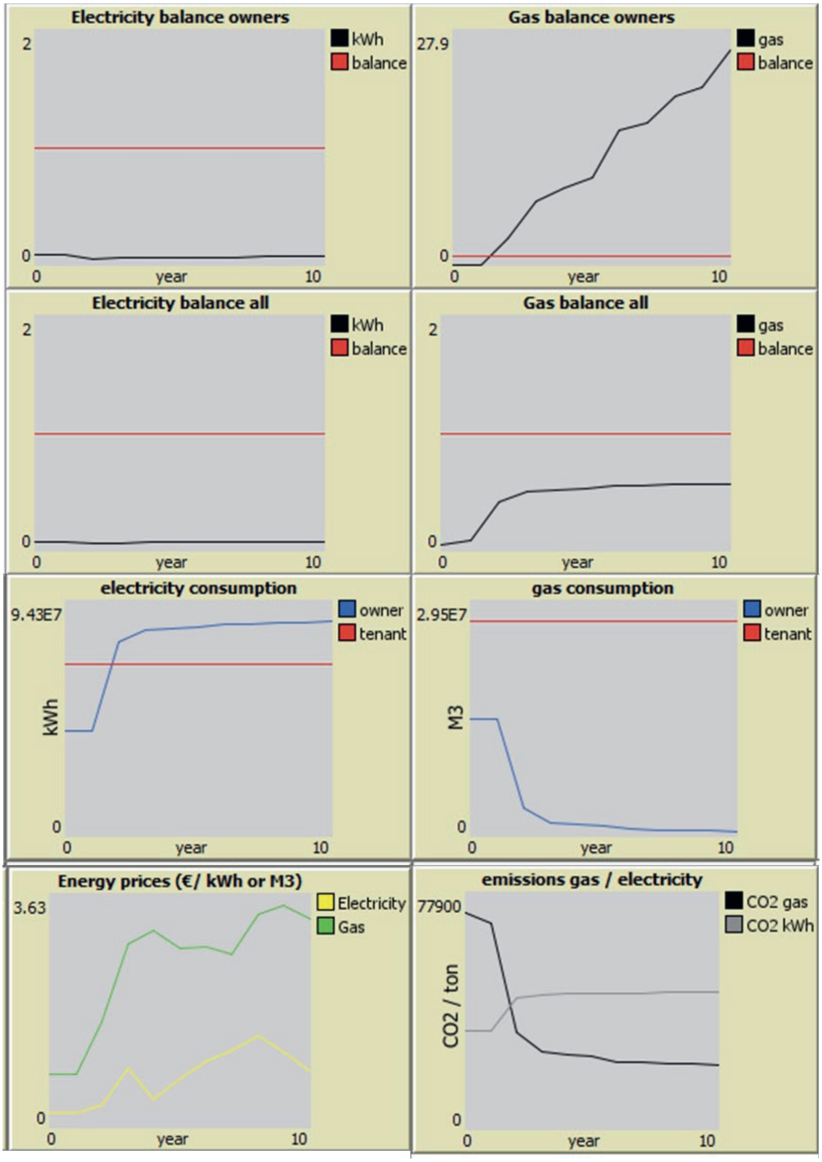


Figure B5. 3. Selected macro variables calculated for Centrum over 10 time steps based on a baseline scenario

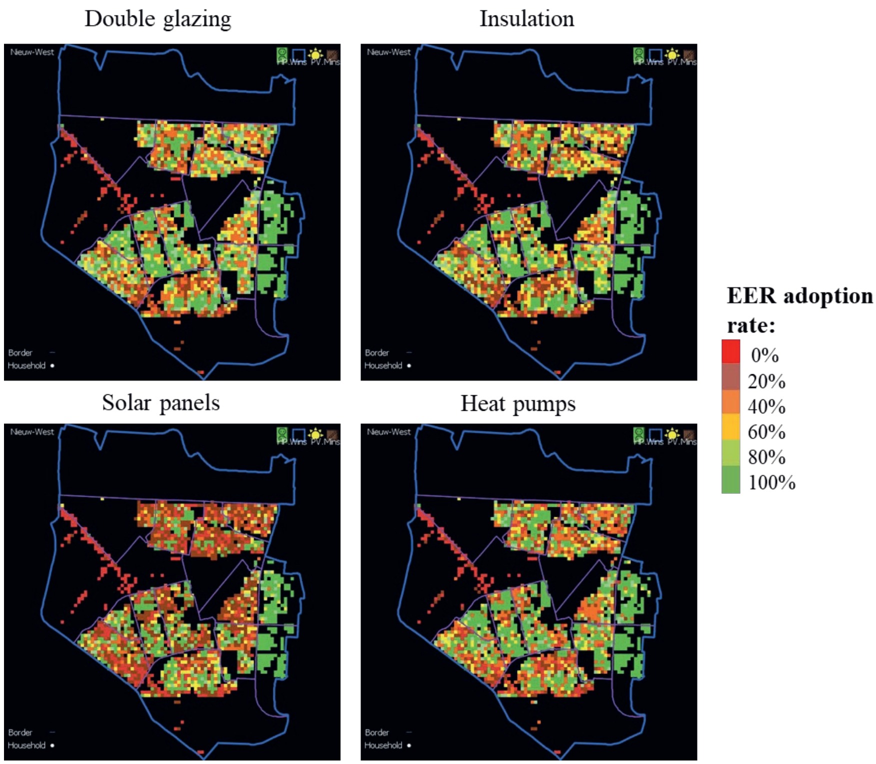


Figure B5. 4. The homeowners' adoption rate of the four EER measures in Nieuw-West by 2030 based on a baseline scenario

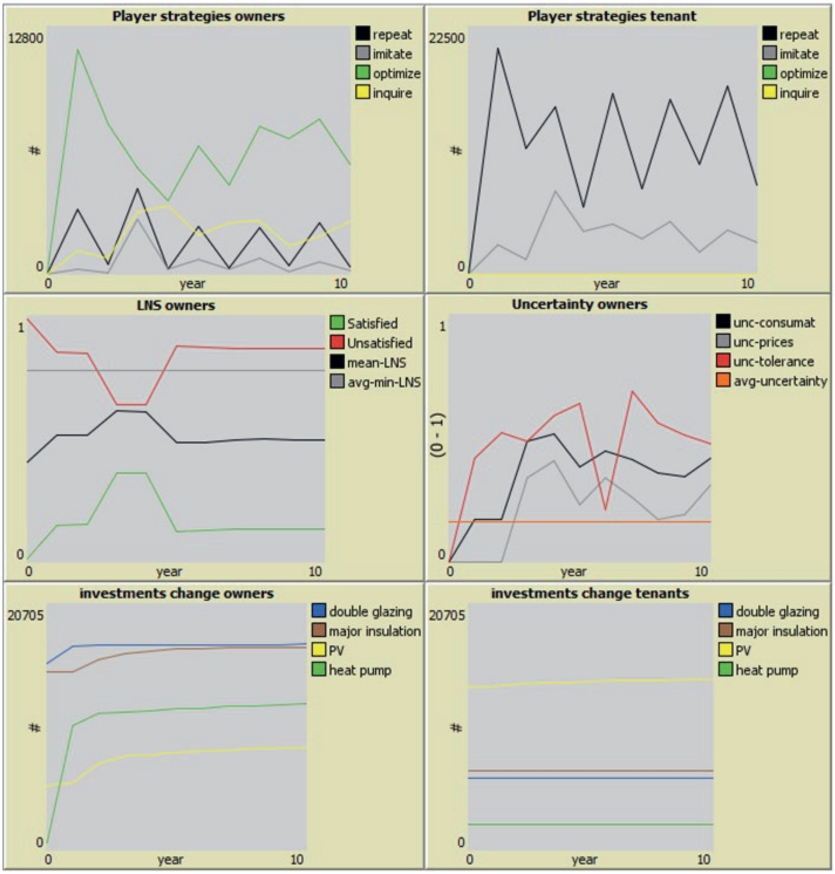


Figure B5. 5. Consumat-related parameters changing over 10 time steps in Nieuw-West based on a baseline scenario

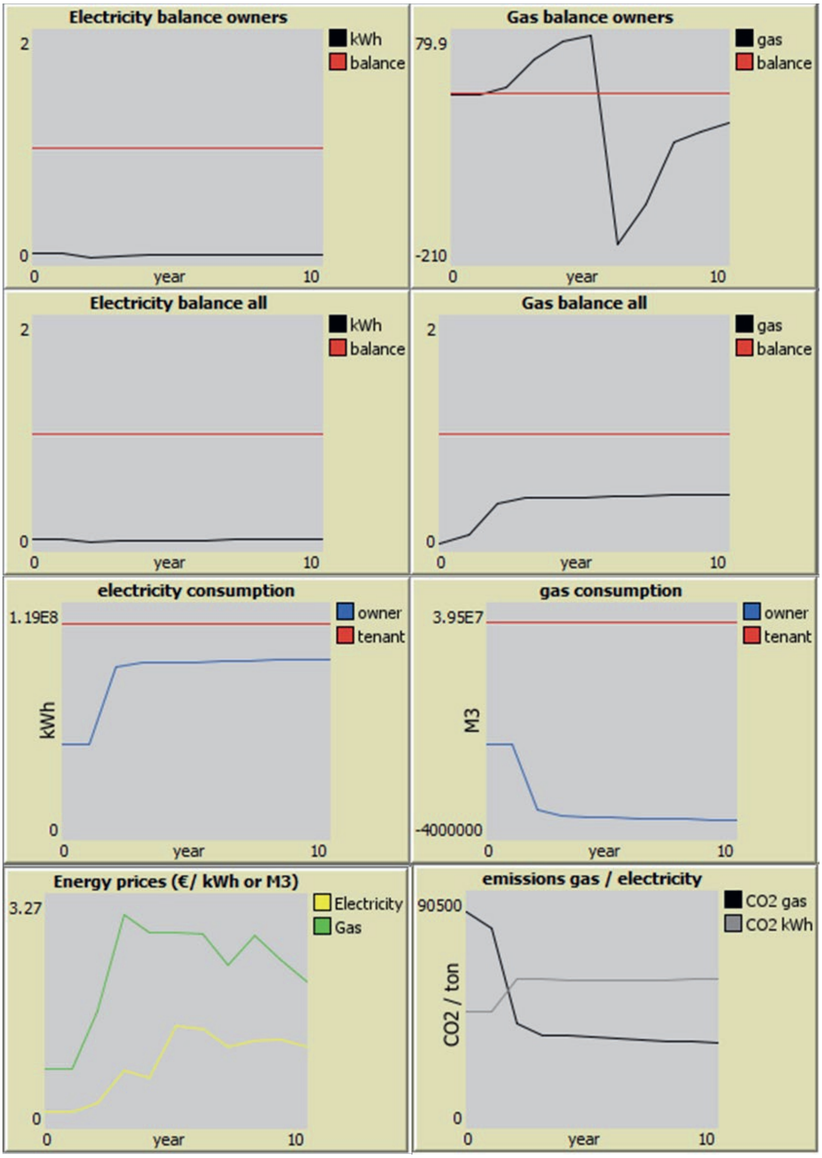


Figure B5. 6. Selected macro variables calculated for Nieuw-West over 10 time steps based on a baseline scenario

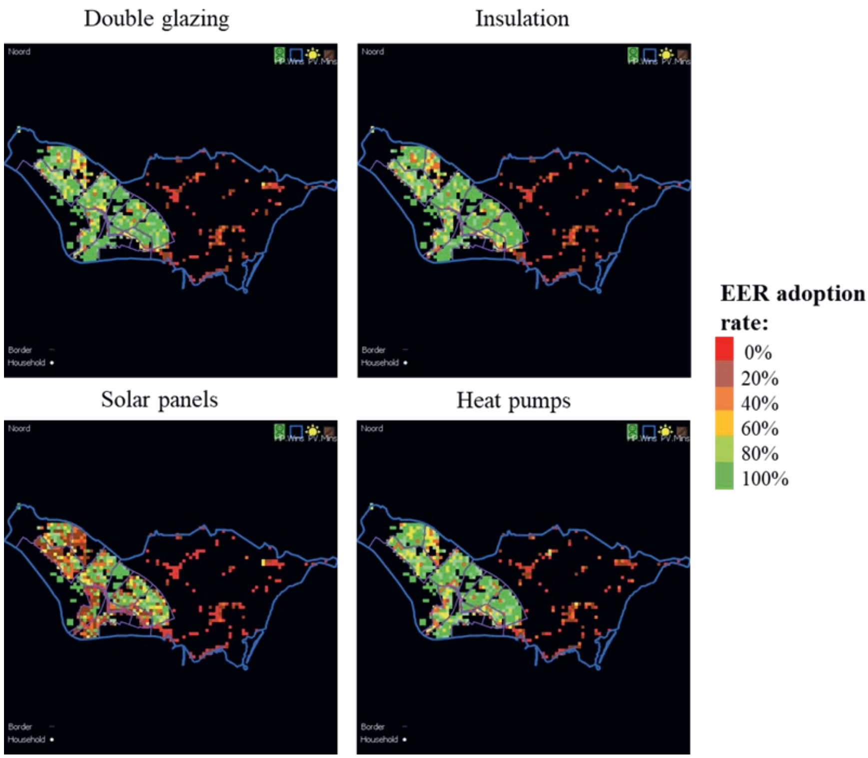


Figure B5. 7. The homeowners' adoption rate of the four EER measures in Noord by 2030 based on a baseline scenario

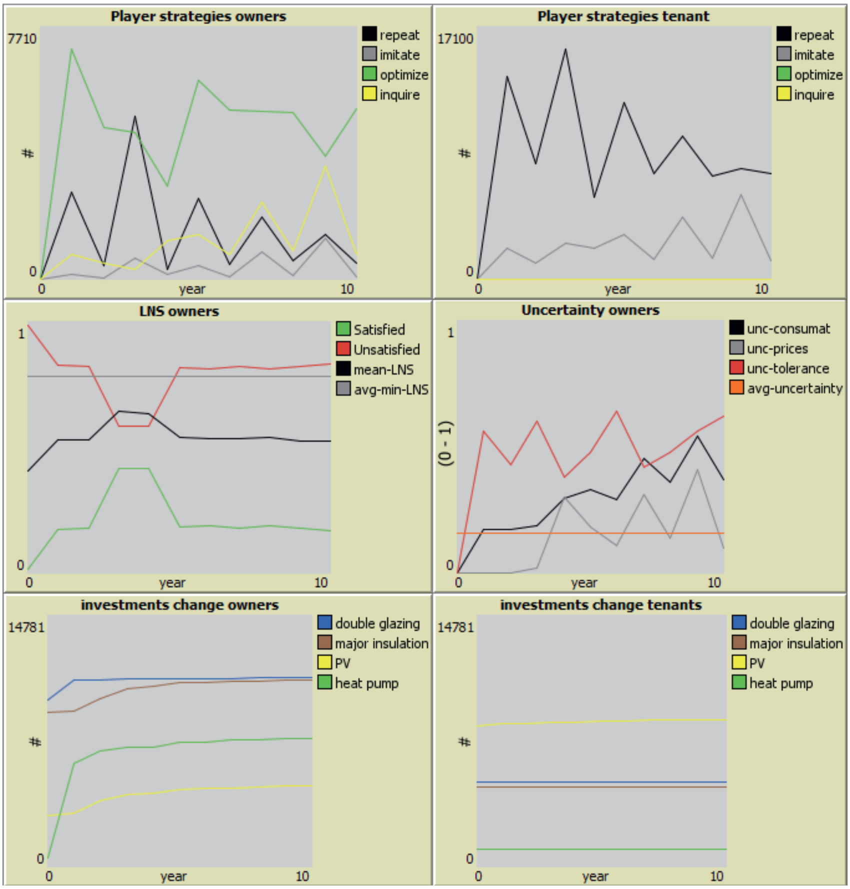


Figure B5. 8. Consumat-related parameters changing over 10 time steps in Noord based on a baseline scenario

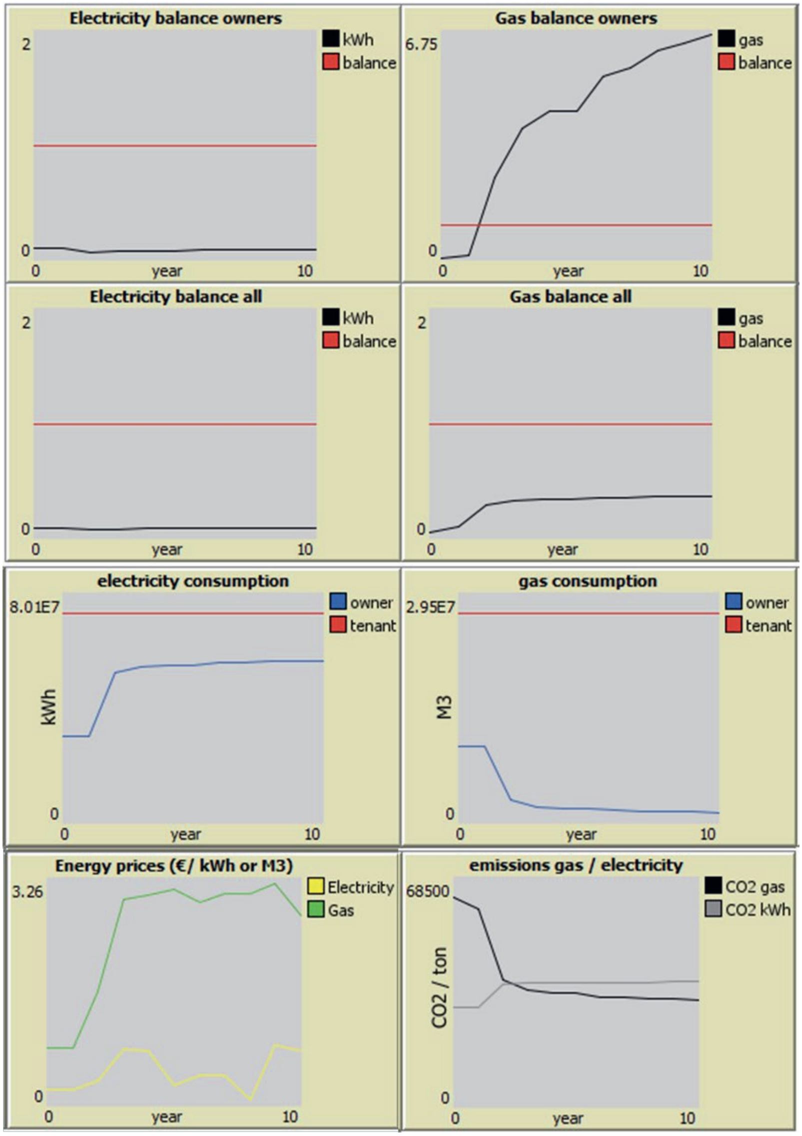


Figure B5. 9. Selected macro variables calculated for Noord over 10 time steps based on a baseline scenario

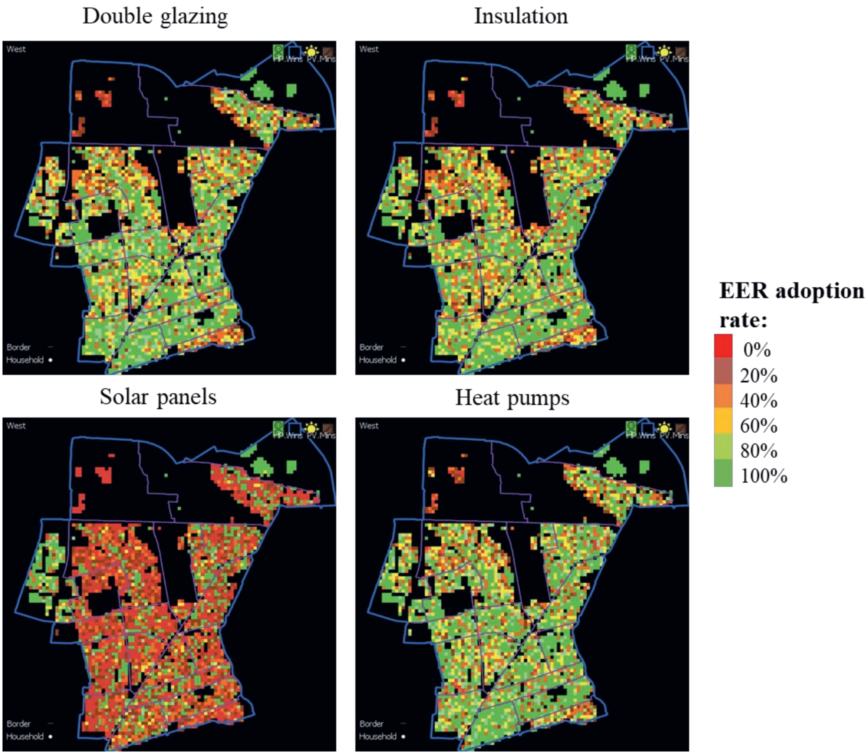


Figure B5. 10. The homeowners' adoption rate of the four EER measures in West by 2030 based on a baseline scenario

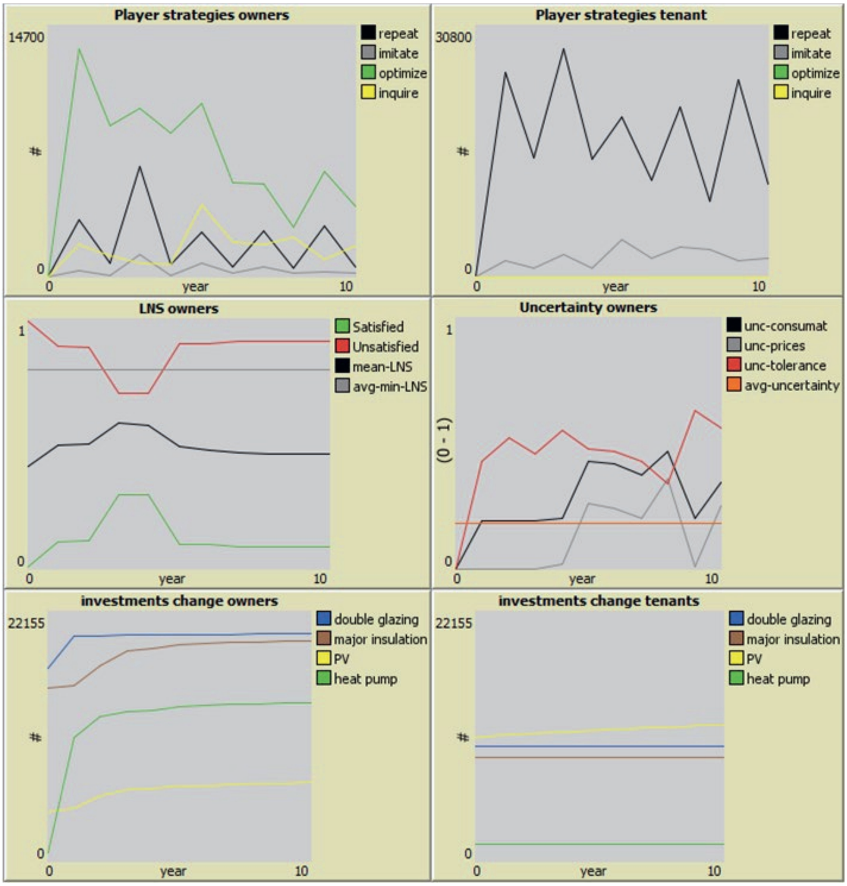


Figure B5. 11. Consumat-related parameters changing over 10 time steps in West based on a baseline scenario

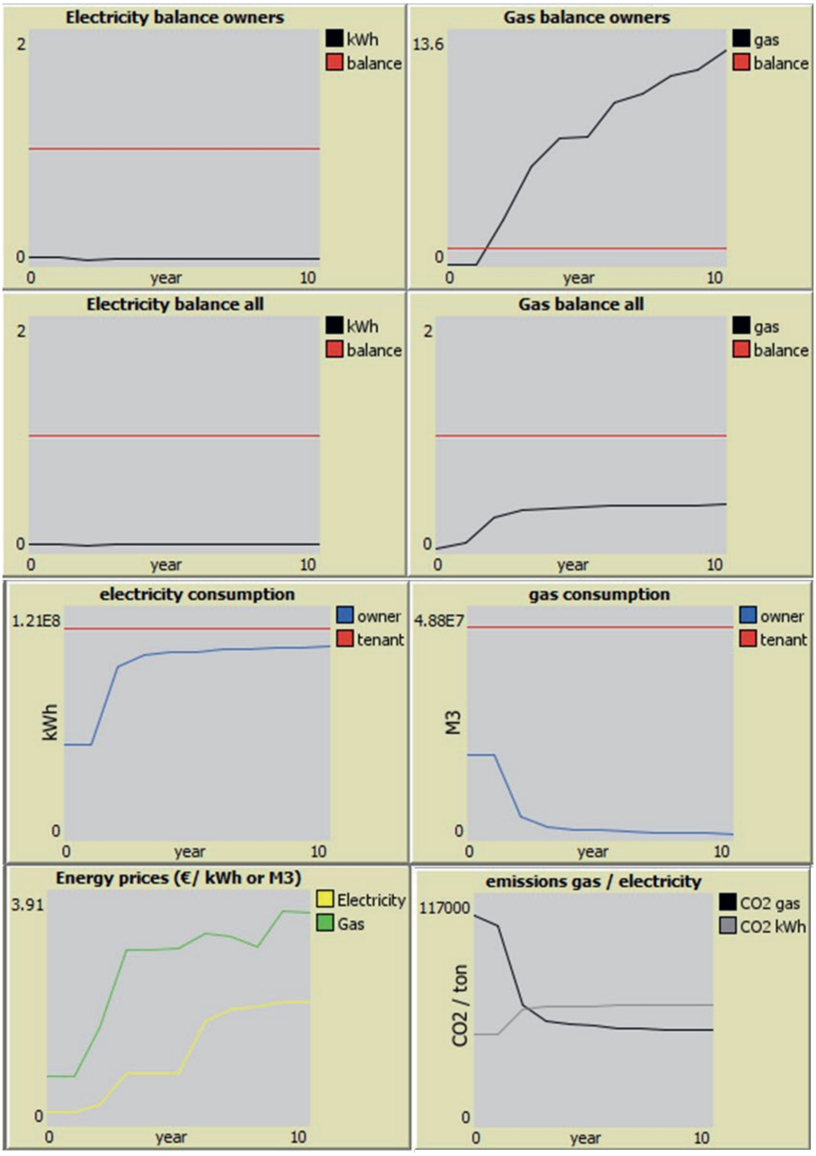


Figure B5. 12. Selected macro variables calculated for West over 10 time steps based on a baseline scenario

Chapter 5

6

Chapter 6

General Discussion

6.1. Introduction

As cities continue to grow and face energy challenges, developing Positive Energy Districts (PEDs) can be a promising solution in the global effort to combat climate change and achieve a low-carbon society. Even though ambitious, PEDs are realistic and already exist across the European region. I have had an opportunity to visit several real-life PEDs, including the Schoonschip neighborhood in the Netherlands, the Torres Vedras town in Portugal, and El Hierro island in the Canary Islands. These PEDs span various geographical scales, yet they share a common objective: the pursuit of the energy transition. Their distinct local contexts have uniquely shaped their journeys toward becoming PEDs. This serves as a compelling case that achieving PEDs is feasible through diverse trajectories.

This dissertation is dedicated to exploring the concept of PED and its pivotal applications in driving the energy transition within urban areas. The overall aim of this research is to explore PEDs pathways toward urban energy transition in Amsterdam by 2030 and craft tailored energy policies that are contextually relevant. Just like putting together a puzzle, this dissertation combines various pieces of research – data, concepts, approaches, and findings – to construct a comprehensive picture of developing PEDs. As a result, the PED puzzle represents a mosaic of backgrounds that can guide the energy transition accounting for local contexts (Figure 6. 1).

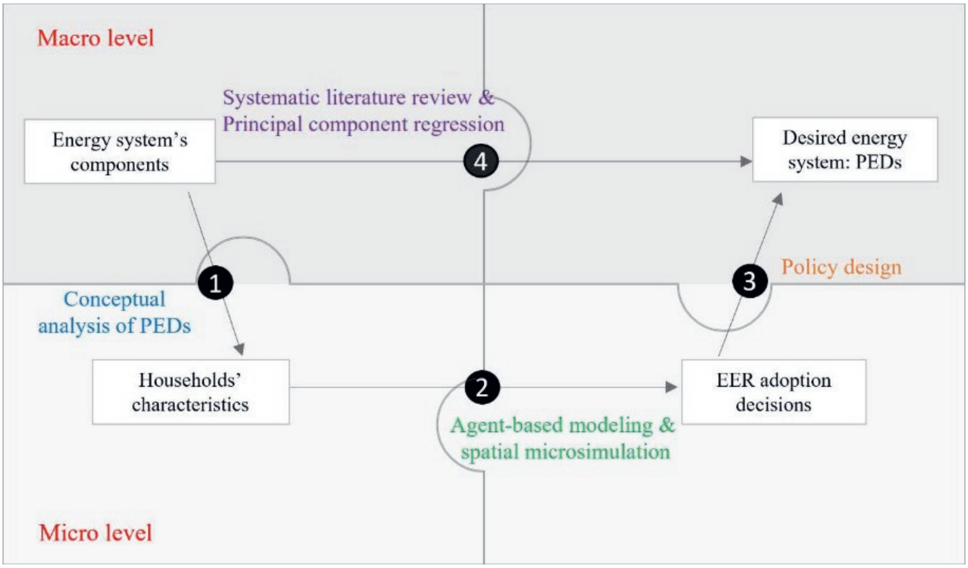


Figure 6. 1. The PED puzzle

Each study in this dissertation shapes this puzzle's contours by delving into different aspects of PEDs and the role of households. Chapter 2 is devoted to uncovering and cultivating a more comprehensive understanding of the PED concept. In Chapter 3, the focus is on identifying factors affecting homeowners' EER adoption decisions in the Netherlands. Chapter 4 centers on explaining the design of the *ENERGY Pro* model, followed by Chapter 5, which explores households' EER adoption decision-making across the districts in Amsterdam and their contribution to the city's carbon emissions reduction goal by 2030. This research adds sociality to advance the understanding of human behavior and interactions in complex systems.

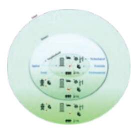
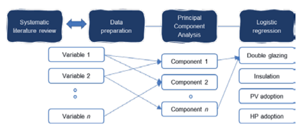
The key findings of this dissertation indicate that Amsterdam's 2030 goal is achievable and there can be different potential PED pathways to reach this goal. The central prerequisites are fostering neighborhood cohesion, including tenants in EER adoption decision-making, and helping the elderly through financial and technical means. These insights emphasize the significance of the human-centric energy transition and the transformative power of collective action.

In this final chapter[36], Section 6.2 presents the synthesis of the main findings of the individual chapters (chapters 2 to 5). Section 6.3 reflects on the theoretical and methodological approaches used in this dissertation, outlining their strengths and limitations. Section 6.4 highlights the contributions of this dissertation to science and society. Section 6.5 and Section 6.6 offer policy recommendations and the roadmap for future research, respectively.

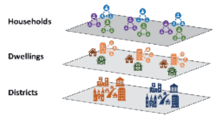
6.2. Synthesis of the main findings

This section presents the synthesis of the main findings of Chapters 2 through 5, highlighting their contribution to this dissertation and to research in general. These chapters are the four pieces of the PED puzzle and aim to thoroughly explore its pathways. Table 6. 1 offers their synthesis.

Table 6. 1. The synthesis of the main chapters

Chapter	Type	Method	Output	Graphical abstract
Chapter 2	Conceptual	Synoptic literature review & case study analysis	A comprehensive view on PEDs: complexity and resilience	
Chapter 3	Empirical	Systematic literature review & principal component regression	Factors affecting homeowners' EER adoption decisions in the Netherlands	

[36] Please note that throughout this chapter, we use "households" and "homeowners" (also "owner-occupied households") depending on the study. This is because some chapters focused solely on homeowners' energy decisions, while other chapters centered on all households' (including tenants') decisions.

Chapter 4	Design	Agent-based modeling & spatial microsimulation	The ODD+D protocol of the ENERGY Pro model	
Chapter 5	Empirical	Agent-based modeling & spatial microsimulation	The output of the ENERGY Pro model in Amsterdam	

6.2.1. Developing a comprehensive view on PEDs

The first piece of the PED puzzle, Chapter 2, lays the foundation for this dissertation by developing a comprehensive view on PEDs. First, synthesizing the concepts similar to PED granted an overview of existing definitions and the key knowledge gaps. Then, reviewing the examples of already implemented PEDs in Europe enabled us to better understand the conceptual and practical differences and similarities. Finally, based on these overviews, we developed a more comprehensive view on PEDs incorporating complexity insight from Complex Adaptive Systems (CAS) and resilience insight from Doughnut Economics.

The key findings of this study include the commonly defined elements of PEDs, contextual factors important for PEDs, and new lenses for viewing and developing PEDs. Based on the review of the existing concept, we identified the defining elements of PEDs: a geographical boundary, state of the interaction with an energy grid, energy supply, and balancing period. These defining elements are mostly similar across all reviewed concepts except for the geographical boundary. The geographical boundary varies between building, neighborhood, or district, depending on the definition. However, it is not limited to a district scale according to the practical examples of PEDs and can be effectively implemented at a larger scale such as “island”. Hence, it is evident that the PED concept can be applied to wider scales and should be defined as an area without being tied to any specific geographical boundary. Also, based on the review of the real PEDs, it is clear that self-sufficient (i.e., autonomous) PEDs are not realistic for the near future due to infrastructural, technological, regulatory, and financial obstacles. On the other hand, dynamic PEDs that interact with neighboring areas are proven effective for most of the areas.

This study also identified contextual factors that are important for developing PEDs. Despite PEDs share similar environmental and social goals, they are path-dependent and differ in their contextual factors. These contextual factors are spatial, technological, economic, environmental, and social (environmental and social contexts should not be confused with the goals that are rather common for all areas). These factors define a status quo upon which each area has to undertake different PEDs pathways. Consequently, it is important to consider these contextual factors when formulating such pathways.

Lastly, this study developed a comprehensive view on PEDs by incorporating insights from CAS and Doughnut Economics views. While CAS offered a lens of systems thinking and complexity, Doughnut Economics contributed through its lens of resilience. These lenses have been missing in the PED concept but are crucial in understanding the energy system. Based on the practical examples, it became evident that PEDs should be understood and approached as complex adaptive systems as they incorporate interacting sub-systems, including technology and agents. These sub-systems evolve over time based on the dynamic rules and changes and impact other parts of the system. Furthermore, Doughnut Economics shares the common environmental and social goals with PEDs and brings in distributive and regenerative dynamics that promote the redistribution of resources (i.e., sharing with others) and their circularity. However, the central contribution of Doughnut Economics to comprehending the PED concept is its notion of the system's resilience through adaptability and transformability. The PED concept has been lacking a discussion on the system's resilience, which is important, especially given the nature of the (renewable) energy system being exposed to disruptions.

This study reveals substantial knowledge gaps and limitations of PED and similar concepts. To address them, we developed a more comprehensive view on PEDs. Based on this view, we call for considering contextual factors that are evidently inherent in real PEDs, developing dynamic PEDs that allow flexibility in the system, and integrating the novel PED Doughnut view in the bottom-up energy transition. Future endeavors in this crucial research field can benefit from investigating the role of electric mobility for energy storage and transport, which can certainly offer new opportunities for PEDs.

6.2.2. Identifying factors affecting homeowners' EER adoption in the Netherlands

The next piece of the puzzle is dedicated to uncovering how the elements of the system can be transformed in a specific context. Chapter 3 examines the factors associated with homeowners' EER investment decisions in the Netherlands based on the WoON Dutch Housing Survey 2021, while the findings in the literature are still inconsistent and contextual. In this study, we first conducted a systematic literature review to identify the potential predictors of EER adoption decisions. Then, we used a principal component analysis (PCA) to reduce their dimensionality (from 25 to 8 predictors) and conducted a logistic regression analysis to uncover further the relationship between the components and EER adoption. The output of the analyses offered a deeper understanding of this relationship and allowed a more meaningful evaluation of this phenomenon within the local context. Based on the results, we outlined possible policy improvements promoting EER adoption among Dutch homeowners.

The key findings of this study demonstrate the importance of neighborhood involvement and the role of previous maintenance, dwelling type in a specific area, and household type in terms of their age and size in EER adoption. Active neighborhood involvement of homeowners living in safer areas and being satisfied with their homes showed a positive correlation with EER adoption, which can be attributed to the impact of the social influence of neighbors. Therefore, a possible policy direction can be supporting neighborhoods with technical, financial, and regulatory assistance, as the neighborhood scale showed promising potential for the bottom-up energy transition. It is also evident that owner-occupied households that previously maintained their house are also more likely to invest in EER as they might be more aware of energy efficiency benefits. Thus, increasing awareness and encouraging combining maintenance and EER adoption by offering financial support (e.g., subsidies, loans) can increase homeowners' motivation to enhance the energy efficiency of homes.

This study also shows that dwelling and area types matter for EER adoption. The analysis shows that multi-family houses in urban areas are still lagging in EER adoption, especially in solar panels adoption. The reason for this might be infrastructural and organizational obstacles such as sharing a common roof with neighbors and the need to agree with them on adoption first. As multi-apartment buildings constitute a major part of the residential built environment in cities, it is important that policymakers revise the regulations on the facilitation of EER adoption in such dwellings. Another point of attention is older, and smaller owner-occupied households that are unlikely to adopt the EER measures as they are often not motivated due to financial and technical reasons. Therefore, governmental support for this population group might be valuable for increasing energy efficiency.

This research sheds light on the factors affecting EER adoption by Dutch homeowners and contributes to the growing body of knowledge in this field by highlighting the importance of the local context. However, this study naturally has some limitations that could be addressed in future research. These limitations are mostly related to the survey data we used for the analysis. First, due to insufficient data, we omitted certain variables that were recognized as significant in the literature from our analysis. Therefore, forthcoming research can benefit from adding socio-psychological factors such as awareness (e.g., regarding energy efficiency and available subsidies), motivations, beliefs, and social influence. The latter is partially incorporated in the present study, however, focusing solely on the influence of immediate neighbors. Considering the influence of family, friends, or other peers might also be important. Second, as the data were collected and released during the COVID-19 pandemic and before the energy crisis of 2022, there might be some deviations in homeowners' decisions due to these system disruptions. Therefore, revisiting this investigation using the future release of the survey will be desirable.

6.2.3. Discovering potential PEDs pathways in Amsterdam

The last two pieces of the PED puzzle, Chapters 4 and 5, are devoted to the agent-based simulation model (ABM) of households' EER adoption decisions in Amsterdam developed by incorporating the views of the PED concept and the factors affecting these decisions. The main purpose of the model was to explore how homeowners make EER adoption decisions in Amsterdam and how these decisions differ across the city districts. Additionally, this study aimed to examine to what extent households in Amsterdam can contribute to the city's CO_2 emission reduction target by achieving PEDs via energy consumption reduction, energy efficiency, and renewable energy generation. Chapter 4 uncovers the conceptual and methodological constructs of the model, while Chapter 5 discusses the implications of the findings and demonstrates various possible pathways that Amsterdam can take toward achieving PEDs.

Uncovering the design, sensitivity analysis, and validation of the ENERGY Pro model

Chapter 4 describes the *ENERGY Pro* agent-based model using the ODD+D protocol, which is a standardized approach to describe the ABMs offering their detailed, easy-to-read documentation. Following the ODD+D protocol, this study uncovers the conceptual framework used for model construction, the spatial microsimulation process of expanding the data, and the model implementation details. This chapter also offers sensitivity analysis, presents validation results, and describes how to use and adapt the model to ensure its robustness and replicability.

The key results of this study include the output of the sensitivity analysis and validation. The sensitivity analysis of the model output was conducted following the one-factor-at-a-time (OFAT) approach. For this analysis, we selected four factors: electricity price, gas price, similarity of households, and their uncertainty level. The sensitivity analysis examined how changes in selected factors affect the EER adoption rates as well as the choice of behavioral strategies in different districts. The key findings based on this analysis demonstrate that higher energy prices, homeowners' connection to similar neighbors, and lower uncertainty of homeowners motivate them to adopt (more) EER measures.

The model's validation has relied on structured interviews with energy experts in Amsterdam. Overall, the experts found the model outputs to be both meaningful and insightful. The key significant points highlighted by the experts encompass existing variations in EER adoption within districts, the role of social influence, as well as the impact of macro-level factors, particularly gas prices. The existing variations in EER adoption, in experts' opinions, are attributed to differences in the characteristics of households and the built environment. These variations are observed at the neighborhood scale, which emphasizes the importance of local context and lower-scale research.

The experts also stressed the significance of social influence, especially that of neighbors. They validated this finding (also observed in the sensitivity analysis) by highlighting the impact of visibility of EER measures such as solar panels and the information exchange that often happens in smaller neighborhood communities. Furthermore, the experts addressed the observed shift in EER uptake subsequent to the alteration in the overall threshold for households' level of need satisfaction (LNS). They emphasized that changes in EER uptake are more likely attributed to macro-level factors rather than solely to the LNS. Notably, a prominent factor that emerged from the experts' interviews was the gas price which also supports the sensitivity analysis result. The experts unanimously agreed that the gas price has been and will remain the most critical factor affecting EER adoption rates in the Netherlands. In addition, they pointed out that the energy price uncertainty of homeowners observed in the sensitivity analysis is closely related to changes in energy prices and can significantly impact their decision-making.

Based on the findings in Chapter 4, the following conclusions can be made. First, conducting contextual lower-scale research on energy transition can help gain a deeper understanding of the dynamics driving the EER uptake. Second, fostering neighborhood cohesion by promoting neighbors' collaboration in PEDs initiatives is crucial for accelerating the local energy transition. Finally, increasing gas taxes along with increasing public awareness about subsidies and energy efficiency, and continuous governmental support can stimulate EER adoption among homeowners.

Analyzing the ENERGY Pro model's output

Chapter 5 presents and analyzes the *ENERGY Pro* model's results. In addition to the model's sensitivity analysis output, the key findings include the variation of EER adoption rates across the city districts and the role of tenants in EER uptake. This chapter reveals that EER adoption rates vary across the districts in Amsterdam due to household heterogeneity and their socio-demographic and dwelling characteristics. Once again, this finding confirms the significance of the local context that has already been evident from the path-dependent nature of PEDs identified in Chapter 2 and the empirical evidence of varying EER uptake in different areas and settings in Chapter 3. Therefore, introducing area- and context-based policy interventions considering the challenges and opportunities of each area is necessary.

Furthermore, this study demonstrates the importance of including tenants in EER adoption decision-making as they can accelerate the energy transition and significantly contribute to achieving carbon emissions reduction goals. Since tenants constitute such a large population group, particularly in urban areas, it becomes imperative for the government to pay closer attention to their plight. Tenants face injustice and vulnerability, especially during times of energy crisis, as they lack legal rights to adopt EER. Addressing this issue presents a critical opportunity for them to overcome the crisis and its consequences and contributes to achieving climate targets.

In conclusion, Chapter 5 reiterates the unequivocal significance of the local context in the process of energy transition. The evidence underscores the necessity for customizing PEDs pathways and energy policy strategies for each district within Amsterdam. Moreover, this study underscores the pivotal role of tenants in enhancing energy efficiency. This insight serves to remind policymakers that tenants as key and large stakeholders group are critical to achieving the energy transition goals in urban areas.

6.3. Reflection on the theoretical and methodological approaches

The core of this dissertation is the *ENERGY Pro* model for achieving PEDs in Amsterdam. This model has been developed conceptually based on the Consumat meta-model and methodologically using agent-based modeling. This section reflects on these two approaches' strengths and limitations observed in this dissertation. In addition, as the model is empirical, it is also necessary to reflect on its validation and the data limitations that have been encountered.

6.3.1. Consumat

Consumat is a comprehensive meta-model designed for studying human behavior and decision-making. The main strength of Consumat is that it is an advanced socio-psychological meta-model that adds sociality to complex studies such as human behavior and decision-making in energy transition. Consumat is developed based on multiple behavioral theories on cognitive processes and driving forces for behavioral dynamics [197]. Therefore, it provides a comprehensive framework for understanding how individuals and groups interact, make decisions, and drive changes within the system. As such, this approach enhanced the depth of this research and analysis of the *ENERGY Pro* model.

Another strength of Consumat is that it incorporates both micro- and macro-level factors, capturing two-directional causation of the system dynamics. This feature allows the model to capture the complex interplay and feedback loops between individual behaviors and larger societal and environmental influences. By accounting for two-directional causation, Consumat provided in this dissertation a more realistic representation of how various factors at different scales influence each other and contribute to the overall energy system dynamics. This approach enhanced the *ENERGY Pro* model's exploratory and explanatory power, making it a valuable tool for analyzing and guiding decision-making in developing PEDs.

However, we also experienced limitations related to Consumat in this dissertation. First, Consumat does not address the culture of agents. Culture profoundly impacts human behavior, decision-making, values, and norms, which can greatly influence EER adoption. Hence, culture plays a crucial role if we want to operationalize the model in different social contexts (e.g., different cities or regions). Addressing this limitation by updating the Consumat framework or using an additional concept on culture would enhance the model's applicability and usefulness in guiding energy transition efforts across various social contexts.

Another limitation was creating social networks of households based solely on demographic variables such as income, age, location, and education. Consumat defines the homophily of agents based on socio-psychological variables such as values and beliefs in addition to demographic ones. Therefore, this limitation is mostly related to the availability of data rather than a specific issue with Consumat itself. Addressing this limitation can provide a better representation and more nuanced understanding of the interactions and dynamics between agents within the model, aligning more closely with the capabilities of Consumat.

6.3.2. ABM

In this dissertation, we have experienced and demonstrated the advantages and opportunities of ABM. The key strength of the *ENERGY Pro* model is that it is spatially explicit and empirically fed, which makes it possible to mimic reality and find targeted and applicable solutions for developing PEDs. This became feasible with the help of the spatial microsimulation method that allowed overcoming the existing data limitations. As such, the combination of social simulation and spatial microsimulation has proven to be a viable approach to addressing data issues and detailed modeling that seemingly improves evidence-based policy.

Another strength of the model is that it unpacks both top-down and bottom-up causations of emergent behavior of the energy system. While the model depicts the impact of changes in macro variables on households' decision changes, it also captures the effect of households' behaviors and interactions on macro-level outcomes. As such, the *ENERGY Pro* model serves a descriptive purpose with an attempt to better understand the underlying dynamics and driving forces of the energy system.

Furthermore, another ABM's advantage is its flexibility and the potential for scenario discovery. Flexibility enables researchers to easily make changes in the model: scale it up or down, adjust parameters' values (e.g., in NetLogo, through sliders, switches, and choosers), and vary the model's running speed and the length of the simulation period. The ABM's flexibility also permits the exploration of different scenarios and "what-if" assumptions. In this dissertation, we initially examined the reality-based baseline scenario. Subsequently, we identified an impactful new scenario, the "Lower LNS_{min}," arising from its results. Lastly, we conducted a speculative "what-if" scenario – the "Tenants inclusion" scenario. These manipulations generated valuable insights into factors affecting the dynamics of the energy transition.

Nonetheless, there are still remaining research and model gaps caused by insufficient data availability and accessibility. The *ENERGY Pro* model falls short in addressing socio-psychological aspects due to the lack of data, making it challenging to establish causality in household decision-making. Moreover, introducing socio-psychological factors affecting the energy-related decisions of households could help examine a rebound effect, which is inherent in energy systems [198]. For example, this phenomenon can be observed when energy efficiency improvements lead to increased energy consumption rather than the expected energy savings.

Another known limitation of ABM is that its calibration and validation often require extensive data. This dissertation also encountered this limitation due to the lack of data. The absence of real-time data on EER adoptions in Amsterdam hindered our model's calibration and validation in refining its accuracy. It will be imperative for the government to take measures to ensure the collection of real-time data in order to obtain an up-to-date overview of the current energy system and plan the transition accordingly.

Finally, running ABM simulations can be computationally intensive, particularly for large-scale models with numerous agents, attributes, and interactions. This substantially limits the scale and scope of ABMs. In this dissertation, we ran the simulation for one district at a time rather than the entire city due to the empirical complexity of the model. This limitation also affects the time required for running sensitivity analysis tests. Presently, due to the computational demands of such simulation models, researchers are constrained to utilizing relatively scarce supercomputers.

6.3.3. Overall reflection

The concept of "sociality" is relatively new and encompasses a complex and evolving understanding of social interactions, behaviors, and dynamics. As society and technology evolve, traditional theories and methods may face challenges in fully capturing and explaining these emerging phenomena. Therefore, while existing theories and methods have their merits, it's important to recognize their limitations and remain open to innovative approaches that can better capture the intricacies of sociality in our ever-changing world. In fact, different approaches and methods serve just as instruments to achieve research goals. Overall, the recognition of the evolving nature of social dynamics is crucial for advancing our understanding of human behavior and interactions and complex systems in general.

6.4. Contribution of this research to science and society

6.4.1. Contribution to energy transition research

This dissertation contributes to energy transition research in multiple ways. First, it contributes to the literature by developing a comprehensive view on PEDs with integrated CAS and Doughnut Economics views. The newly developed view can effectively serve as a blueprint for holistic energy transition addressing its complexity and the need for resilience. Second, this dissertation offers a deeper understanding of factors affecting Dutch households' EER adoption decisions that serve as a backbone for developing targeted area-based policies. We addressed a limitation in the literature caused by controversial findings on factors associated with EER adoption decisions using principal component regression and offered a more meaningful interpretation of the results. Third, this dissertation also contributes to energy research by offering an empirical spatially explicit simulation model of the urban energy transition in Amsterdam. The *ENERGY Pro* model stands out for its design, applicability, and significant societal impact. The model offers an extensive framework covering multiple EER measures, addressing sociality, and demonstrating the combination of ABM and spatial microsimulation. Furthermore, it provides a deeper understanding of the macro- and micro-level dynamics in the energy system and its transition. Finally, this dissertation contributes to the energy transition research by providing targeted context-based policy recommendations that could be a useful addition to the current policy schemes in Amsterdam and beyond. These policy recommendations are especially valuable for their evidence-based nature and inclusiveness.

6.4.2. Contribution to society

This dissertation also contributes to society by positioning it at the center of the energy transition. First, it focuses on a human-centric pathway such as PED Doughnut. The PED Doughnut view addresses pressing issues such as climate change and energy crises and ensures social and environmental well-being without leaving anyone behind. Even though the benefits of this view can be fully realized in the future, its more inclusive and conscious goals are timely and relevant. Furthermore, by examining households' energy-related behavior and decision-making, this dissertation evaluates their potential contribution to the carbon emissions reduction goal in Amsterdam by 2030, a milestone for the residents and the city to mitigate climate change. Additionally, this dissertation also contributes to achieving the Sustainable Development Goals including (7) Affordable and Clean Energy, (11) Sustainable Cities and Communities, and (13) Climate Action, by promoting energy consumption reduction, an increase in energy efficiency and renewable energy production, and alleviating energy poverty. These actions not only influence the preservation of the environment but also enable saving financial means. Last but not least, this dissertation contributes to society by showcasing how the urban energy transition can be approached in practice (in the example of the city of Amsterdam) with households playing a key role. It highlights the importance of bottom-up energy transition initiatives led by people, neighborhood collaboration and cooperation, and governmental support in financial, technical and technological, regulatory, and informational terms.

6.5. Policy recommendations

Energy policies play a significant role in the energy transition, as the adoption of energy efficiency measures and renewable energy technologies still necessitates considerable financial investments and significant infrastructural and behavioral adjustments. Therefore, inclusive and targeted energy policies are indispensable in driving and supporting the transformation toward a sustainable and low-carbon energy landscape. Based on the findings of this dissertation, the following policy recommendations are proposed to foster PEDs development and build stronger local energy communities:

1. *PEDs should be developed using an area-based approach* and aiming to include all stakeholder groups. The area-based approach means allowing different combinations of policies that would target and include diverse groups in PEDs development, taking into account their local (spatial) contexts. Based on the *ENERGY Pro* model output, it became

evident that there are differences in the EER adoption rates across neighborhoods in a district, which indicates the importance of considering their contextual differences. As such, taking into account the challenges and opportunities of each area as well as the heterogeneous characteristics of different population groups, can help design more effective energy strategies and interventions that are tailored to the needs of each area.

2. *The government should provide financial, technical, regulatory, and informational support*, especially to vulnerable population groups (e.g., elderly, energy poor, tenants), to stimulate the EER adoption and facilitate the energy transition for these groups. Drawing upon the findings of this dissertation, a distinct trend emerges wherein the EER adoption rate proves to be notably higher among homeowners with advanced educational backgrounds and higher income brackets. It is also evident that homeowners' uncertainty about energy prices lowers the likelihood of EER investments. Consequently, it is imperative for the government to prioritize initiatives aimed at *increasing awareness* and extending guaranteed *financial support* for EER adoption that can help curb uncertainty. In addition to financial help, it is evident that older population groups need foremost *technical support* in EER implementation. Finally, multi-family dwellings lag behind in adoption as they tend to have complex renovation processes caused by the need to agree with multiple owners. *Revising regulations* to facilitate EER adoption in such dwellings will be imperative.

3. The findings of this dissertation confirm that homeowners living in newer houses do not tend to implement EER measures because of the perception that their homes are already energy-efficient enough, which is not always true. Also, houses in the Netherlands are obliged to have an energy efficiency label only when being built, sold, or rented [199]. This evidently leaves a large number of houses with a lack of energy efficiency and motivation for its improvements. Therefore, the government should require all homeowners to *obtain an energy efficiency label* as it is obligatory now for all office buildings [200].

4. Tenants play a significant role in the urban energy transition, as they constitute the largest energy consumer group. Unfortunately, they do not have legal rights in making EER adoption decisions, which impedes achieving the energy balance and, consequently, the PEDs development. To overcome this issue, it is essential to *include tenants in the EER adoption decision-making* process (as landlords may lack the motivation to implement EER in properties they do not occupy) and encourage them to actively invest in adopting these measures. It is also important to support them with information and, if necessary, financial means as they are important drivers in the energy transition.

5. As energy transition is a collective effort, local neighborhood communities play a key role in advancing PEDs. This dissertation identifies that the more similar neighbors are more likely to mimic each other's EER adoption behavior. Therefore, *fostering neighborhood cohesion* by encouraging social bonding and a sense of belonging through creating opportunities for neighbors to interact is essential. One of the examples can be

organizing community events such as sports tournaments or neighborhood festivals. In addition, it is also important to promote collaboration and cooperation among neighbors and support local initiatives, which in turn can also contribute to the local energy transition.

6. The *ENERGY Pro* model demonstrates the increase in EER adoption rates caused by increasing gas prices. As gas prices rise, it becomes more expensive for households to heat their homes, which incentivizes them to seek EER solutions to save energy and costs. Therefore, *increasing taxes on gas usage* can motivate households to adopt the EER measures. However, it is crucial that such an intervention is implemented along with increasing public awareness, technological advancement, and access to financial resources (e.g., subsidies and loans) to ensure a just and inclusive energy transition. In turn, collected gas taxes could be used for EER subsidies to support those who cannot afford it.

7. This dissertation encountered several constraints caused by data limitations on the adopted EER measures in Amsterdam. The absence of a legislative mandate for seeking permission before adopting EER measures in residential buildings has led to a scarcity of real-time data on households that have already implemented such measures. This data gap not only hinders comprehensive research in the field of energy transition but also restricts policymakers from accessing valuable insights into the actual adoption rates. Therefore, it would be advantageous for various stakeholders, including researchers and policymakers, if *mandatory reporting on the adoption of EER measures* by households is enforced.

Overall, these policy recommendations developed based on the data-driven evidence provided in this dissertation hold the potential to serve as a crucial foundation for devising a well-informed transition strategy. Policymakers can effectively steer the energy transition in Amsterdam in a promising direction, capitalizing on the identified opportunities and addressing the underlying challenges. These policy measures offer a path toward a greener, more resilient, and inclusive energy future, where environmental preservation and societal well-being are harmoniously balanced.

6.6. Avenues for future research

This section explains the multifaceted ways in which the trajectory of future research can deepen our understanding of the energy transition and foster interdisciplinary collaboration across diverse domains.

1. *Collecting data on socio-psychological variables and addressing a rebound effect*

In future research, collecting data on socio-psychological variables and incorporating these aspects into the *ENERGY Pro* model would be important. This will be crucial for a better understanding of energy-related behavior and decision-making and for uncovering their causality. In addition, it will also be valuable to address a rebound effect that often sparks controversy over energy transition actions. The rebound effect can occur when efforts to improve energy efficiency, reduce energy consumption, and transit to renewable energy result in offsetting effects leading to higher (conventional) energy use than initially anticipated. It is also crucial to acknowledge that the government's objectives may diverge from those of households.

2. *Incorporating electric mobility and digital technologies*

Another necessary direction for future research is examining and incorporating electric mobility as it can offer new opportunities for developing PEDs, as noted in Chapter 2. Electric mobility can contribute not only to a cleaner environment but also serve as a storage battery enabling energy flexibility. As this dissertation focuses on the case of the Netherlands, and Amsterdam in particular, where storage batteries are not yet common, this aspect fell outside of this work's scope; however, remains an important future research perspective. This direction is promising as the capacity of storage batteries of electric vehicles is increasing [201], and it can play a transformative role in developing PEDs. In addition, digitalization also plays an instrumental role in achieving energy system flexibility and energy use optimization. As such, digital technologies can help individuals and communities coordinate various elements of PEDs, including renewable energy generation, energy efficiency, energy storage, and electric mobility [202], and empower their active participation and collaboration in achieving the common energy goal.

3. *Including other energy stakeholders and setting up a living lab*

Another important direction for future research is incorporating other stakeholders in the PEDs model to gain a more holistic understanding. Local energy stakeholders are not limited to individuals/households and communities but also include other parties such as energy companies (e.g., energy producers, energy suppliers/distributors, energy service companies), government bodies, and housing corporations. In addition, it can be beneficial to set up a living lab that is designed as a dynamic and collaborative real-world environment. This setting can help simulate the development, adoption, and scaling up of sustainable energy solutions, and consecutively, test and evaluate them where stakeholders play a central role. The living lab can be an important addition to future research to observe, understand, and learn about the different roles and contributions of various energy stakeholders.

4. *Incorporating culture*

Incorporating culture into the *ENERGY Pro* model is another promising direction for future research. This expansion holds the potential to refine the model's functionality across diverse social landscapes, making it more adaptable for a wide range of applications and ensuring its accuracy. The integration of cultural factors not only enhances the model's explanatory capabilities but also strengthens its relevance in policy formulation. This enhancement can lead to a deeper understanding of the intricate interplay between human behavior, cultural nuances, and the complex processes of energy transition. Therefore, the inclusion of culture in the model broadens its utility and delves deeper into the intricacies of energy transition within various social contexts.

5. *Conducting an infrastructural spatial analysis*

Finally, another perspective recommended for future research is conducting an infrastructural spatial analysis. This dissertation incorporated a spatial layer with the neighborhood location of households in Amsterdam, which allowed us to analyze the households' differences across the neighborhoods and districts and their EER adoption rates. However, future research can also benefit from adding another spatial layer that would incorporate the energy system's technical aspects, such as the distribution of resources and infrastructure. Spatial analysis can play a pivotal role in optimizing energy efficiency and clean energy installations, identifying suitable locations for them, and analyzing energy use patterns and the role of distance at the local level. Therefore, conducting an infrastructural spatial analysis can further contribute to informed policies and decision-making in the energy transition.

PEDs signify a paradigm shift in urban energy planning, offering a pathway toward a sustainable, low-carbon, and resilient future. The perspectives on future research discussed in this section have the potential to further uncover the intricacies of PEDs and contribute to extending the PED puzzle. The PED puzzle possesses the capacity to encompass not only additional dimensions but also be collected and adapted to different contexts.

Summary

At the dawn of a new millennium, the conventional systems falter. The energy system is not an exception. Given the context of the climate and energy crises, the current energy system is inefficient and outdated. The aim of this study is to find environmentally friendly, human-centric, and sustainable solutions to this predicament. This dissertation explores such solutions for the energy transition, employing Positive Energy Districts (PED) as a guiding concept. More precisely, the dissertation examines potential PED trajectories within the context of the Netherlands, considering the country's intermediary climate and energy targets set for attainment by 2030. The research employs a backcasting approach. This means it begins with defining a desirable future and then works backward to the present to identify necessary steps.

Chapter 1 presents theoretical and conceptual approaches applied in this dissertation as well as methods for addressing the research objectives. The section on theoretical and conceptual approaches starts with the central concept of this dissertation – the PED concept. At the core of the concept is the goal to achieve energy efficiency, energy sufficiency, and energy flexibility within an urban area. However, as this concept is still relatively new and has limitations, this section also discusses the usefulness of adding the lenses of Complex Adaptive Systems (CAS) and Doughnut Economics. These lenses contribute to the PED concept's comprehensiveness by adding layers of complexity and resilience. Finally, this section presents Consumat, the key meta-model for understanding human behavior and decision-making and the interaction dynamics in the system.

The methods in this dissertation are presented following the lines of thinking of Coleman's boat, differentiating macro-level and micro-level outcomes. The main methods used in this research include conceptual analysis, systematic literature review, principal component regression, and agent-based modeling. The results of the conceptual analysis and the literature review served as a reminder of the suitability of Coleman's boat for explaining the methodological approach of this dissertation. This diagram features two levels that are inherent to complex systems. Principal component analysis (PCA) is a correlational approach that involves analyzing micro-level data at the macro level. On the other hand, agent-based modeling (ABM) is a micro-level modeling technique that offers a bottom-up approach to explain macro-level outcomes through causal relationships. The ABM is the central method used in this dissertation to investigate households' energy-efficient retrofitting (EER) decision-making. It is a computational modeling approach to simulate complex systems by representing individual agents and their interactions within an environment. The chapter concludes by outlining the dissertation structure and offering a table with an overview of the main chapters of this dissertation.

Chapter 2 lays the foundation for this research by exploring the emerging concept of PED and its pivotal role in driving the energy transition and achieving climate neutrality. This chapter pursues the objective of establishing a cohesive understanding of PEDs, focusing on their application in European urban residential areas while offering insights applicable to diverse contexts. Existing parallel concepts aim to enable buildings, neighborhoods, or districts to fulfill energy needs from cost-effective, locally accessible, eco-friendly renewable sources. However, inconsistencies among these concepts identified in this chapter underscore the need for a more comprehensive framework. Consequently, this study undertakes a comprehensive analysis of the PED concept, guided by an examination of pertinent literature and practical PED instances.

The literature review involves the analysis of existing PED and similar concepts across geographical scales, defining components and metrics crucial for conceptualization and operationalization. On the other hand, the analysis of real-world PEDs demonstrates that they often transcend the boundaries set by conventional definitions, highlighting the oversight of intrinsic contextual factors. To rectify these differences across the literature and practice, this chapter develops a more comprehensive view on PEDs by adopting the CAS and Doughnut Economics approach. This holistic approach becomes especially relevant in fortifying the complexity and resilience of the energy system, which is vital for navigating its transition and potential disruptions. By scrutinizing the concept's boundaries, complexities, and potential pitfalls, this chapter serves as a critical foundation for an enriched understanding of PEDs and their significance in advancing sustainable and resilient urban energy landscapes.

Chapter 3 delves into the crucial realm of EER decisions within households, a primary domain in developing PEDs. In this dissertation, EER includes measures such as insulation of windows, roof, walls, and floor, as well as the adoption of heat pumps and solar panels. The chapter uncovers valuable insights by analyzing Netherlands data via principal component analysis and binary logistic regression. The findings underscore distinct factors shaping EER choices. Notably, older and smaller owner-occupied households with longstanding residential ownership and occupancy exhibit lower propensities to adopt heat pumps, solar panels, and insulation technologies. To counteract this trend, it is recommended that the government extends financial and technical support to empower the elderly to enhance the energy efficiency of their dwellings. In contrast, homeowners actively engaged in fostering neighborhood cohesion exhibit higher tendencies to invest in solar panels and insulation. This phenomenon highlights the pivotal role of communal participation, implying information exchange and mutual encouragement as catalysts for EER adoption. Consequently, this chapter stresses the significance of community cooperation and streamlined information dissemination. Accordingly, it recommends government-led awareness campaigns and enhanced information accessibility and underscores the importance of supporting local neighborhood energy initiatives through financial, technical, and regulatory help. These insights not only emphasize the imperatives of elderly assistance and the neighborhood influence within the Netherlands but also offer broader applicability, informing energy policies across diverse contexts.

Chapters 4 and 5 zoom in on Amsterdam and focus on homeowners' EER-related decisions in the city and their contribution to Amsterdam's goal to reduce carbon emissions by 55% in 2030 compared to the level in 1990. **Chapter 4** introduces the *ENERGY Pro* agent-based model, employing the Overview, Design Concept, and Details + Human Decision-making (ODD+D) protocol. Designed with empirical specificity, the model's primary objective is to explore the decision-making dynamics of homeowners in Amsterdam regarding their adoption of EER measures. The *ENERGY Pro* model is spatially explicit and covers seven districts of Amsterdam. The temporal resolution of the model corresponds to one year (one time step) covering a period of 10 years (2021-2030).

Following the ODD+D framework, this study documents the model's conceptual and methodological architecture. Conceptually, the model relies on Consumat, which is an advanced socio-psychological meta-model developed based on multiple behavioral theories on cognitive processes and underlying driving factors for behavioral change. Households choose one decision strategy out of four – imitate, optimize, repeat, or inquire, depending on their need satisfaction and uncertainty each time step. They can make individual or collective decisions depending on the measure they adopt. Methodologically, the modeling process uses a combination of agent-based modeling and spatial microsimulation. Agent-based modeling is used to build the model itself, while spatial microsimulation is utilized to expand the data for input in this model. This chapter elaborates on the details of model implementation.

This chapter provides sensitivity analysis and expert validation results to ensure the model's credibility and robustness. It also guides users through the model's practical application and adaptation, ensuring its replicability and accessibility for other researchers. As such, this study extends an invitation to the broader research community to utilize and customize the *ENERGY Pro* model. By demonstrating the usefulness of social simulation and spatial microsimulation combination, this chapter offers a valuable tool for investigating the energy transition.

Chapter 5 offers an analysis of the outcomes yielded by the *ENERGY Pro* model. Central to the findings is the observation of diverse EER adoption rates across the districts within Amsterdam. These disparities are caused by household heterogeneity, encompassing their socio-demographic and dwelling characteristics. This stresses the importance of neighborhood-scale analysis of the local energy transition. Notably, this finding echoes the path-dependent nature of PEDs discussed in Chapter 2 and the empirical evidence spotlighting varying EER uptake across distinct areas and settings, as presented in Chapter 3. Another key finding in this study is that households' adoption decisions are affected by their similar neighbors' adoption decisions, with the degree of similarity among neighbors further increasing this impact. This finding underscores the role of social connections in shaping EER adoption behaviors. Chapter 5 also highlights tenants' important role in achieving the city's carbon reduction target. Tenants in Amsterdam are the largest residential group, and their involvement in EER adoption decision-making has the potential to significantly accelerate the energy transition. Based on these results, Chapter 5 concludes by proposing policy recommendations. This study underscores the necessity for nuanced policy strategies accounting for the local context in each district within Amsterdam and fostering neighborhood cohesion. It also emphasizes the pivotal role of tenants in enhancing energy efficiency. The insights from this study can also be useful for other similar cities.

Chapter 6 concludes this dissertation by offering a general discussion of the findings, theoretical and methodological approaches used, and outlining this work's contribution and policy recommendations. This chapter starts with the synthesis of the main findings from Chapters 2 through 5. It delves into their specific research aims, methods, and results. Another section of this chapter offers a reflection on the main theoretical and methodological approaches used in this dissertation. This section focuses on Consumat and ABM and thoroughly discusses their main strengths and limitations encountered in this dissertation. Chapter 6 also presents the contribution of this dissertation to research and society by outlining its novelty and applicability. This chapter concludes by offering policy recommendations based on the main findings and presents avenues for future research.

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About the author

Erkinai Derkenbaeva was born (1993) and raised in Bishkek, Kyrgyz Republic, along with her three siblings, two elder sisters, and a younger brother. She grew up in a family where both her parents dedicated their entire lives to academia.

She obtained her bachelor's degree in Economics and Management from the Kyrgyz-Russian Slavic University in 2015. In 2016, she gained her first master's degree in Economic Governance and Development from the OSCE Academy in Bishkek. As part of her thesis, she did an internship at GIZ (German development agency) in a project focused on Mineral Resources for Development. During her internship, she visited remote regions to conduct field research based on which she wrote her thesis on the impact of mining on regional sustainable development. She continued her journey at GIZ as a project assistant in the Civil Society Fund project with the main focus on monitoring and evaluation of implemented development projects with societal impact.

In 2017, she was granted a European scholarship to pursue her second master's degree in Comparative Local Development, which she obtained in 2019. She worked on her thesis during her internship at IOS (Leibniz Institute for East and Southeast European Studies), focusing on the analysis of the transition of the Central Asian countries toward an inclusive green economy. Following the completion of her degree, she received an invitation to join the Urban Economics chair at Wageningen University and Research to embark on her Ph.D. journey. During her Ph.D. program, she has also been part of the EU research and training project focusing on Positive Energy Districts, mainly involved in the business models domain of the energy transition. As of October 2023, Erkinai is employed as a research fellow at Amsterdam Institute for Advanced Metropolitan Solutions and as a postdoctoral researcher at her already home chair – Urban Economics at Wageningen University.

Erkinai Derkenbaeva
Wageningen School of Social Sciences (WASS)

Completed Training and Supervision Plan

Name of the learning activity	Department/Institute	Year	ECTS*
A) Project related competences			
A1 Managing a research project			
WASS Introduction Course	WASS	2020	1.0
Writing the research proposal	UEC, WUR	2019-2020	6.0
Scientific Writing	Wageningen In'to Languages	2020	1.8
'Positive Energy Districts: Mainstreaming Energy Transition in Urban Areas'	WASS PhD day	2021	0.5
'Positive Energy Districts: Mainstreaming Energy Transition in Urban Areas'	International Conference on Environmental Psychology, Siracusa, Italy	2021	1.0
'Analysis of energy-related investment decisions of households in Amsterdam' *'Future images of PEDs: vision, engagement to a pathway, key challenges of implementation'*	Reinventing the City, Amsterdam, The Netherlands (online)	2022	1.0
'From CONSumers to PROSumers: spatially explicit agent-based model on achieving Positive Energy Districts (paper presentation)	Social Simulation Conference, Milan, Italy	2022	1.0
'Positive Energy Districts: a pathway toward urban energy transition' (doctoral student award presentation)	French Regional Conference on Complex Systems, Le Havre, France	2023	1.0
Visiting researcher	Graduate Workshop in Computational Social Science, Santa Fe, The USA	2023	2.0
A2 Integrating research in the corresponding discipline			

Agent-Based Modelling of Complex Adaptive Systems, INF 50806	WUR	2020	6.0
1st and 2nd Winter Schools on leveraging knowledge and transferable skills, empowering global citizens, and innovation clinic	Smart BEEjS project	2020	9.0
B) General research related competences			
B1 Placing research in a broader scientific context			
Seminar series on writing and cross-cultural management	Smart BEEjS project	2020	0.3
Seminar series on Experimental Economics	Smart BEEjS project	2020	0.5
Seminar series on Comparing Regulatory Frameworks for PEDs	Smart BEEjS project	2020	0.5
Seminar series on Energy Economics	Smart BEEjS project	2020	1.0
3rd Winter School on vision and challenges of PEDs, business development, and career perspectives	Smart BEEjS project	2022	3.0
B2 Placing research in a societal context			
Value Generation by PEDs: Best Practices Case Study Book	Smart BEEjS project	2020	2.0
Scenario-based Foresight Regional Interviews	Smart BEEjS project	2021	1.0
Value Generation Systems for PEDs: Foresight Report	Smart BEEjS project	2022	1.0
C) Career related competences/personal development			
C1 Employing transferable skills in different domains/careers			
Career Orientation	WGS	2022	1.5
Circular Economy, teaching (practicums)	BMO, WUR	2020, 2021, 2022	1.0
Economics and Governance of Energy Transition, teaching (visiting lectures)	UEC, WUR	2020, 2021, 2022	1.0
Supervising a bachelor student	INF, WUR	2020-2021	1.0
Total			**44.1**

*One credit according to ECTS is on average equivalent to 28 hours of study load

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