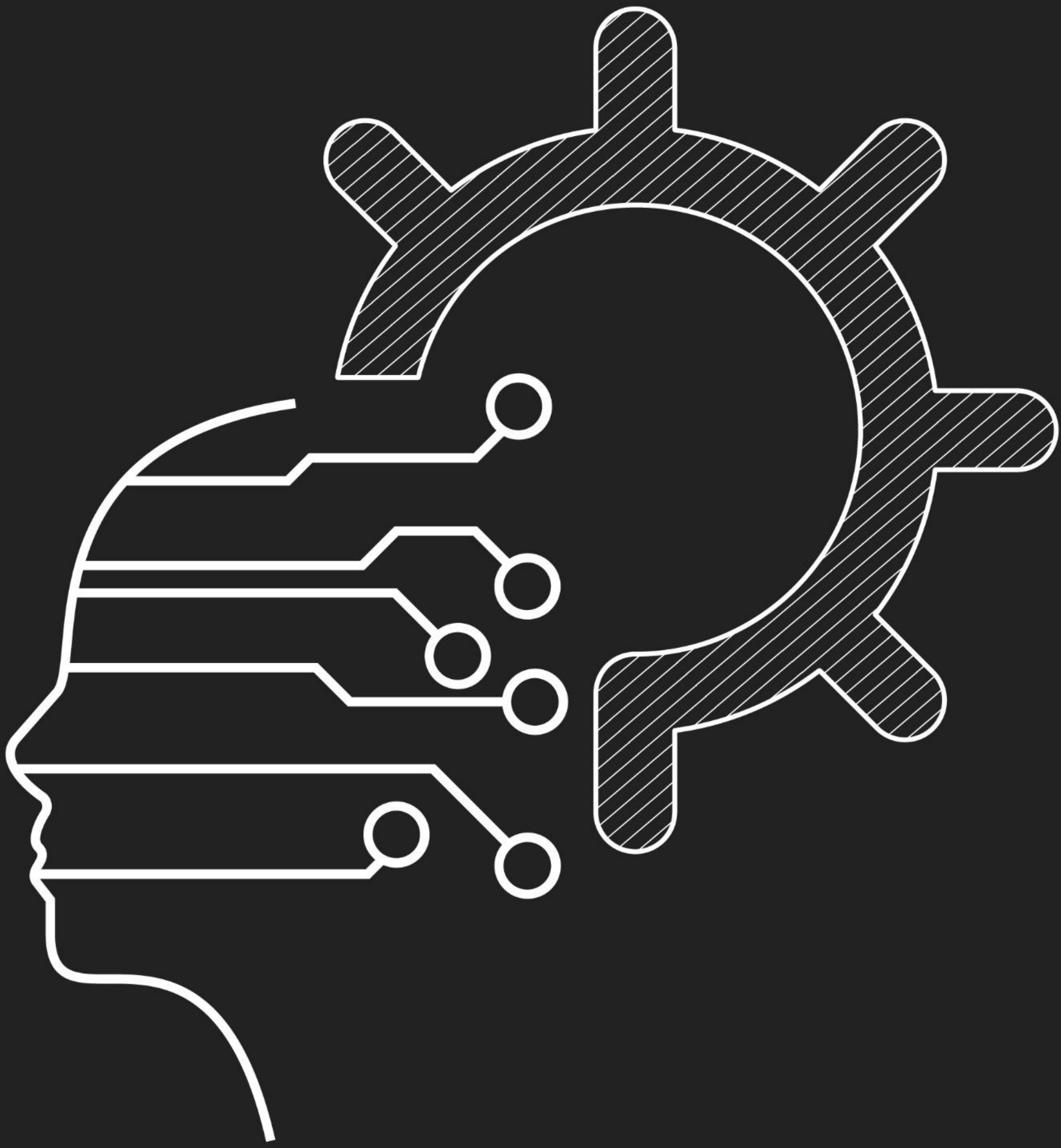

Understanding Household Solar PV Adoption: An Innovative Approach with Large Language Models

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Understanding Household Solar PV Adoption:

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A thesis submitted in partial fulfillment of the requirements for the degree of

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Abstract

Residential solar photovoltaic (PV) systems play a crucial role in energy transition and climate change mitigation in urban areas. However, the adoption process shows social disparities, raising concerns about energy justice. Current research has limitations in understanding the complex mechanisms behind household solar adoption decisions. Therefore, this study explores using large language model (LLM)-based agents to simulate household solar adoption decisions.

Based on a literature review, we developed a framework covering four key factor categories: technical attributes, household characteristics, personal beliefs, and external contexts. We created an LLM-based household agent model (PVAgent) that converts influencing factors into structured prompts, expanding from individual decision-making to multi-agent systems, with both decisions and reasoning statements as output. Using three neighborhoods in Amsterdam as a case study, we simulated solar adoption behavior across different social groups. Using three neighborhoods in Amsterdam as a case study, we simulated solar adoption behavior across different social groups.

The result shows that the LLM agent model can generate reasonable individual decision logic and group-level structural patterns. It also shows how household adoption dynamics change over time with evolving motives and barriers. Based on these insights, we propose three principles for future policymaking: comprehensive strategic frameworks, structural innovation, and differentiated approaches for specific groups.

In summary, this research contributes by introducing LLMs to energy behavior modeling. Although there are limitations, such as the subjectivity of prompt design, this research provides an innovative approach to understanding complex household decision-making. Future studies can further develop this approach and explore more extensive application scenarios with advanced methodological integration and interdisciplinary cooperation.

Keywords: *Solar photovoltaic adoption, large language models, agent-based modeling, energy transition, energy justice*

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While this research certainly has limitations, it represents a courageous venture into uncharted territory. I must confess that even completing the thesis on schedule came as a surprise to me. The four-month journey of working by day and researching and writing by night and on weekends felt really overwhelming but also fulfilling, like a rebirth. I am proud of what I accomplished. I am grateful to myself and to my friends and family for their support from far away.

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Terms and Acronyms

PV	Solar photovoltaics
LLMs	Large language models
GenAI	Generative artificial intelligence
ABM	Agent-based modelling
RAG	Retrieval-augmented Generation
DOI	Diffusion of Innovation Theory
TPB	Theory of Planned Behavior
VBN	Value-Belief-Norm Theory
TAM	Technology Acceptance Model
UTAUT	Unified Theory of Acceptance and Use of Technology
KNN	K-Nearest Neighbor

Chapter 1 Introduction

1.1 Background

The transition toward renewable energy has become widely accepted as a critical solution for global challenges like energy security and climate change [1]. Urban areas, which consume approximately one-third of global energy, have positioned residential solar photovoltaic (PV) systems as a key solution to energy transition efforts [2], [3], [4]. These residential rooftop PV systems can be easily integrated into already-existing urban built environments, benefiting residents' health and economy, as well as reducing greenhouse gas emissions and air pollution [5], [6]. As a result, the global adoption of household solar PV systems has grown significantly in recent years. Several factors drive this growth, including falling costs and advancing technology [7]. Policy support and financial incentives from many countries have also contributed, including feed-in tariffs and net metering policies [8], [9], [10].

Despite the rapid growth in household solar PV adoption, concerns about equality in the energy transition are increasing. As noted, inequalities are inevitable in energy transitions and may lead to or worsen socially unjust outcomes [11], [12], [13]. In this context, energy justice has emerged as a new field of research [14]. This concept usually includes representation and inclusion in the decision-making process, as well as the fair allocation of energy service costs and benefits among various socioeconomic groups [15]. Another influential framework comes from McCauley et al.[16], who identified three key dimensions of energy justice: distributional justice, recognitional justice, and procedural justice.

A systematic literature review by Jenkins et al. [14] shows that solar energy is one of the most studied energy technologies in energy justice research. Many studies have shown that social stratification significantly affects residential solar PV adoption. Several disadvantaged groups face higher adoption barriers. These include low-income households [17], [18], [19], [20], ethnic minorities [21], and social housing residents [19], [21], [22]. In addition to socioeconomic factors, urban environmental features and spatial layouts also contribute to these adoption disparities [18], [23].

Understanding household decision-making behavior is essential for promoting justice in household PV adoption. This understanding helps identify specific barriers that prevent different groups from adopting solar technology, which may cover a range of elements such as financial, technological, informational, and sociocultural aspects [24], [25], [26]. Detailed analysis of household solar PV decision-making can also reveal structural problems in current policies and programs. For example, studies suggest that some incentive schemes could unintentionally exacerbate income disparity, while some housing subsidy may overlook the requirements of renters [27]. Therefore, understanding the decision-making process therefore enables the development of more equitable participation approaches and inclusive policy actions [25], [28], [29].

Despite many studies have examined factors that influence household solar PV adoption, there are still methodological barriers to comprehending these complex decision-making processes [30]. While previous research has recognized the complex mechanisms underlying PV adoption [31], conventional research methodologies struggle to integrate multiple factors at the same time. With more emphasis on socioeconomic characteristics (such as income and ethnicity), their relationship between environmental factors, policy framework, and social networks is sometimes oversimplified [29]. Many other factors affect households as they gather information, consider options, and make decisions. However, traditional statistical techniques and basic agent-based models cannot effectively capture this dynamic and context-dependent process [32]. Furthermore, most research concentrates on macro-level analyses at the city or district level due to data collection limitations, failing to fully examine variations in decision-making behavior at the household level [33]. These methodological limitations highlight the need for new modeling approaches to better understand and simulate household behavioral patterns in solar energy adoption.

In recent years, Generative AI (GenAI) has become one of the most important technical developments. It can generate content that closely resembles human-produced work [34], [35]. Large Language Models (LLMs) are particularly promising within this field, which offer new opportunities for understanding household solar PV adoption complexity. Due to their advanced natural language processing and text production capabilities, LLMs show human-like environmental observation and decision-making abilities [36], [37]. These features allow for sophisticated role-playing functions, which motivates researchers to investigate LLM-based agents for creating virtual environments to simulate social phenomena. Compared to traditional agent-based modeling methods, LLM-based agents provide a number of advantages. They can enable sensitive interactions between agents [40], replicate more complex decision-making logic without explicit rules for reasoning [39], and integrate various information and data sources [38]. They are therefore particularly suitable for simulating decision-making behavior. Also, their technological scalability and zero-shot generalization capabilities enable fine-tuning for adoption to a variety of contexts and research topics [38]. For example, this technology has been applied in fields such as personal travel behavior [39], classroom scenarios [40], and social networking [41].

These advances provide new possibilities to improve our understanding of how households make decisions about using solar energy. However, LLM-based agents also have limitations and challenges. Their robustness remains uncertain, and their applicability to specific tasks needs exploration [42], [43]. On the other hand, their resource consumption and computational efficiency present problems for large-scale applications [44]. Like other AI-driven methods, they also face limitations such as privacy concerns and hallucination [44], [45]. Therefore, the potential application value of these technologies in the specific field of solar PV adoption remains to be explored.

1.2 Research Aims and Questions

In order to offer new insights for promoting just energy transition, this study aims to explore how LLM-based agents can be used to model household decision-making processes in solar PV adoption. Theoretically, this study will examine the various factors that impact solar adoption a across different groups and how these factors interact. This will provide new insights to explain disparities in household PV adoption and energy transition patterns. In terms of methodology, this project will investigate how this new approach can be used in household energy decision research. With the development of an LLM-based agent model, this research intends to provide empirical support for developing more inclusive policies and fostering a more equal energy transition by simulating and understanding the decision-making of various households.

Specifically, this research aims to address the following research question:

How can LLM-based agents be used to simulate and understand household decision-making in solar PV adoption?

To systematically address this main question, the research is structured around three related sub-questions:

- **What factors influence household decisions on solar PV adoption?**
- **To what extent can LLM-based agents effectively simulate household decision-making processes for solar PV adoption?**
- **How can simulation results from LLM-based agents inform policy recommendations for solar PV adoption?**

The first question establishes fundamental knowledge of adoption dynamics by examining multidimensional factors. This provides crucial inputs for the modeling framework. The second question then addresses the methodological challenges while converting the theoretical knowledge into optionable models. The third one, which comes last, is about analyzing simulation results and turning them into practical policy suggestions. These three questions approach the study from interrelated perspectives: input, implementation, and output. They integrate theoretical understanding with real-world applications to promote a more equitable energy transition.

1.3 Research Scope - Amsterdam as A Case Study

This study focuses on Amsterdam as a case study. Amsterdam is a highly representative case in residential solar PV adoption. In addition to setting aggressive goals for renewable energy, the city has put in place several measures to encourage the use of solar PV in residential buildings. As a densely populated city with diverse architectural forms, Amsterdam faces common technical, economic, and social challenges in promoting distributed PV systems. Its experience provides important insights into the energy transition of other cities. Furthermore, a strong basis for carrying out this research is provided by Amsterdam's extensive data sharing as well as its rather open policy-making process. By methodically examining Amsterdam's circumstances, we aim to provide universally applicable insights for understanding and advancing urban energy transitions.

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Chapter 2 Theoretical Background and Conceptual Framework

2.1 Solar PV Adoption Decision-Making

2.1.1 Evolution of PV adoption research

Adoption of solar PV is not a fresh area of study. Various disciplines, such as sociology, economics, and psychology, have contributed to the interdisciplinary nature of research in this field [1]. The evolution of studies on residential solar PV adoption reflects our deepening understanding of this complex household decision-making behavior.

Research in this field started in the 1980s, when distributed PV was still in its early stages. Most studies focused on technical and economic factors, while some employed the Diffusion of Innovation Theory (DOI) to explain early adopters' motivations [2], [3]. Since the 2010s, solar PV installations have expanded quickly due to cost reductions and technological advancements. In this period, research attention has shifted toward a more comprehensive understanding of adoption behavior [4]. As a result, theories from social science and economics have been integrated into this research field. According to the literature review by Ashraf Fauzi et al. [5], theories including the Theory of Planned Behavior (TPB), Value-Belief-Norm Theory (VBN), and Technology Acceptance Model (TAM) have been introduced in this research field. This reflects the recognition that complex interactions between social, economic, and psychological factors influence PV adoption decisions [6]. Around 2020, awareness of social inequalities in PV adoption began to rise. This resulted in increasing attention to distributional disparities and barriers faced by vulnerable groups. Since then, research on residential PV adoption has also taken energy justice concerns into account [7].

In terms of methodology, statistical analysis has long been the dominant approach. Modeling and simulation have become the second most popular methods in this field due to rapid developments of agent-based modeling and spatial analysis since the 2010s [8]. In recent years, artificial intelligence and machine learning have also been integrated, providing new opportunities to understand the socioeconomic complexities behind variations in PV adoption [9].

However, developing comprehensive frameworks remains challenging.

In a systematic review of 173 papers, [10] pointed out that a significant problem is the lack of frameworks that successfully combine different predictive factors toward PV adoption. There are other limitations in current research methods. They primarily focus on final adoption behavior, while overlooking the process of attitude and the influence of behavioral control factors. Besides, model analysis are overly simplistic and direct, which often lacks depth and innovation [8].

To better understand the development and current state of research on household PV adoption decisions, the main theories and research methodologies in existing literature will be discussed in the following sections.

2.1.2 Key theories of household decision-making process

As summarized by [8], frequently employed behavioral theories and models in this research field include the Diffusion of Innovation Theory (DOI), the Value-Belief-Norm Theory (VBN), the Unified Theory of Acceptance and Use of Technology (UTAUT), the Theory of Reasoned Action (TRA), the Technology Acceptance Model (TAM), and the Theory of Planned Behavior (TPB). Among these, DOI, TPB, and VBN are the most commonly used.

DOI is one of the first theories applied to residential PV adoption research. This theory analyzes five key factors (relative advantage, compatibility, complexity, trialability, and observability), and classifies users from innovators to laggards to explain how new technologies spread within social groups [11]. The practical application of this theory was further advanced by [12], who integrated spatial analysis to reveal the impact of peer effects on household solar diffusion curves. A study conducted in India showed that the relative advantage, observability, and compatibility of solar PV devices significantly influenced consumers' behavioral intentions, which in turn had a positive impact on adoption [13]. The adoption of solar PV is also influenced by sociodemographic and economic factors, as well as individual motivations, according to research by [14]. The study further highlights that adopters, potential adopters, and non-adopters have different motives and perspectives. However, DOI does have certain limitations. It attributes the non-adoption of innovations to individuals while overlooking structural and contextual barriers that may hinder adoption [15]. Furthermore, it fails to explain people's deeper psychological decision-making processes, such as sense of responsibility and environmental awareness [16].

Research on solar adoption has also extensively used the Theory of Planned Behavior (TPB). Proposed by Ajzen [17], TPB emphasizes that an individual’s behavior is influenced by three main psychological factors: attitudes, subjective norms, and perceived behavioral control. In the context of household PV adoption, attitudes reflect household's positive or negative evaluations of PV adoption and their environmental awareness; subjective norms relate to social networks and peer influences; and perceived behavioral control involves how households perceive their capacity to purchase and install PV systems, including affordability and home ownership [18]. However, TPB has limitations in terms of static decision-making and ignores the impact of emotional processes and feelings on individual energy decisions, as it is based on the rational choice of utility maximization [19], [20].

VBN offers an alternative perspective by emphasizing the importance of moral obligations and environmental values in adoption decisions. According to VBN theory, pro-environmental behavior is driven by a causal chain that begins with relatively stable value orientations, progresses to specific beliefs about environmental conditions and human responsibility, and finally activates moral standards that guide action [21]. Research indicates that households with strong environmental values and a sense of responsibility toward climate change are more likely to adopt PV systems [22]. However, it is important to recognize that although respondents cite environmental factors as one reason for installing solar systems, this is by no means the sole driver [23].

It is evident that each of these theories has specific strengths and limitations in explaining the decision-making behavior. Given the complexity of PV adoption decisions, researchers are attempting to integrate multiple theoretical frameworks. [24] combined variables from the VBN, TPB, and DOI theories to explain consumer interest in residential PV. They categorized these predictors into several major groups, including technology-specific beliefs, personal dispositions, external influences, values, and household constraints. Similarly, [6] integrated perceived behavioral control from TPB, personal intentions from VBN, and product perception from DOI to propose different variant models.

These approaches acknowledge that household decision-making is influenced by multiple factors, including individual characteristics and external contexts. Based on these frameworks, the variables from the aforementioned theories can be classified into four dimensions: technology attributes, external context factors, personal beliefs and intentions, and individual (household) characteristics (see Figure 2-1). This approach produced a more comprehensive picture of household decision-making.

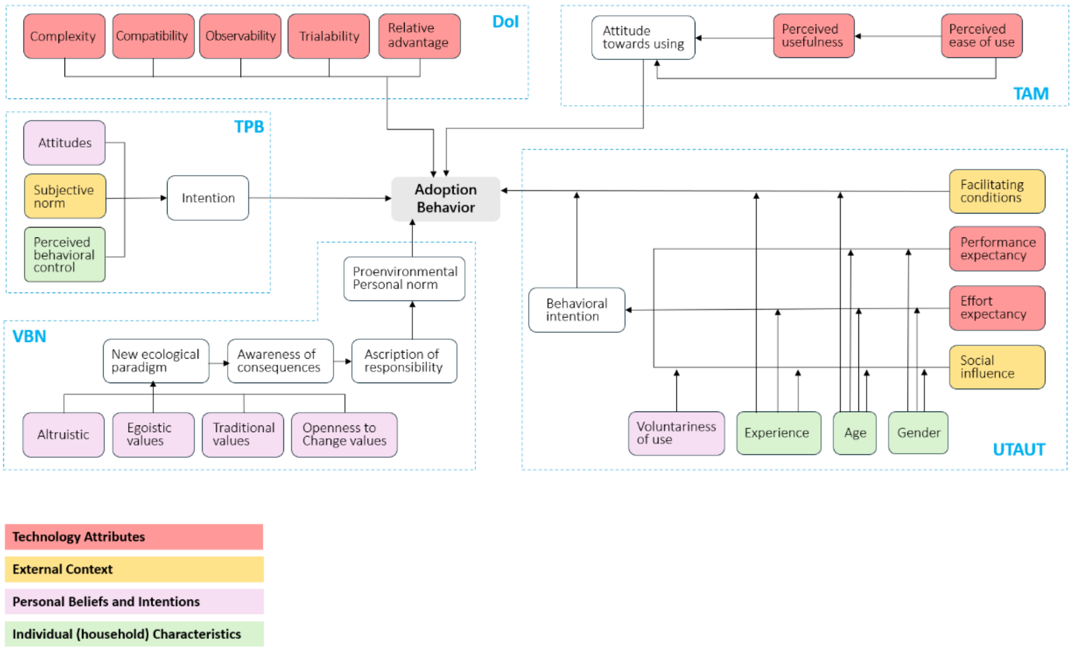

Figure 2-1 Theories related to household decision-making and variable categorizations

Although these research and integrated frameworks offer valuable insights into how households make decisions, modeling and analyzing how these multiple factors interact in real-world situations remain challenging. This complexity is amplified when accounting for the varied conditions experienced by different social groups. This highlights the need for advanced methodological approaches that can handle both complex factor interactions and cross-population variations.

2.1.3 Current research methods and limitations

As previously mentioned, the primary research methodologies in residential solar PV adoption research include statistics, modeling, simulation, and qualitative analysis.

The most common method has always been statistical analysis, including econometric approaches and regression [8]. These methods usually rely on quantitative surveys and cross-sectional or panel data [25]. Statistical analysis is excellent at finding connections between socioeconomic variables and adoption outcomes in big datasets to determine the main elements impacting adoption decisions [6]. However, this approach often struggles to capture the dynamic nature of the decision-making process and the interactive relationships between different factors.

The second most popular approach is modeling and simulation, especially agent-based modeling (ABM) and spatial analysis [8]. In practice, these two methods are often combined. For instance, a hybrid AMB based on a GIS platform was developed to model the neighborhood-level market diffusion of rooftop solar PV installations [26]. Similarly, [20] developed the ENERGY Pro model, which simulates building energy retrofit decisions in Amsterdam by incorporating geographical and social layers. These approaches provide tools for assessing neighborhood effects and social factors. To be specific, ABM allows researchers to simulate how individual decisions aggregate to generate adoption patterns at the neighborhood scale while considering temporal variations [27]. However, current ABM implementations usually rely on fixed and oversimplified decision rules that cannot accurately capture the complexity of household decision-making, particular regarding social and psychological aspects.

Machine learning techniques have also been increasingly used in PV adoption studies in recent years. They offer new capabilities for pattern identification and predictive modeling and are particularly advantageous when dealing with unknown relationship and nonlinear functions. For instance, [9] applied conditional inference trees (CTREE) after analyzing four other machine learning algorithms, and their results helped to clarify some conflicting findings from earlier research. However, the black box nature of these techniques might limit their applicability for policy insights by making it difficult to understand the underlying decision mechanisms.

Additionally, qualitative methods like interview provide valuable insights. They can offer a more profound comprehension of individuals' decision-making processes and their motives, preferences and barriers [13], [28]. However, sample size, representativeness and possible discrepancies between expressed preferences and actual behavior are some of the challenges of these qualitative approaches.

These current methods also share some common limitations. First, the generalizability and granularity of study findings are often influenced by limitations in data collection and the inaccessibility of micro-data. Second, most approaches find it difficult to integrate various theories and data types, making it challenging to capture the dynamic interactions between social, psychological, and institutional factors while maintaining explainability. As a result, emerging methodologies such as LLMs provide new opportunities to solve these constraints and better understand household solar energy adoption decisions. The advantages of these approaches will be discussed in the next section.

2.2 Large Language Models as Decision-Making Agents

2.2.1 Characteristics of LLMs and LLM-based agents

Generative artificial intelligence (GenAI) represents one of the most significant developments in artificial intelligence technology in recent years, with its ability to generate or synthesize contents that is often indistinguishable from human-created ones [29], [30]. This advancement has been significantly facilitated by models such as transformers, language models, diffusion models, and generative adversarial networks [31]. GenAI has been widely applied across diverse disciplines, such as art, education, biology, architecture, construction and engineering (ACE), significantly influencing several types of businesses as well as society in general [30].

GenAI also shows great potential in urban planning. According to [32] and [33], incorporating AI into urban planning procedures is essential for addressing urban growth-related challenges, improving residents' quality of life, and achieving smart and sustainable development. [34] conducted a systematic study into the use of AI in local governments and found four primary uses: data analysis and decision support, automation and efficiency enhancement, predictive scenario analysis, and citizen participation. [35] further note that GenAI offers promising support for urban research and management, especially in smart city development. This is due to its advantages in data augmentation, synthetic data and scenario production, and three-dimensional urban modeling. Similarly, the analysis of [36] shows that data processing, communication, and automation are the main areas where AI excels in urban planning. This potential possibility has been generally recognized by urban administrators, despite some present challenges [37].

Large language models (LLMs) are one of the main driving models in recent applications. LLMs are the most recent paradigm in language modeling. They have developed from earlier models such as neural and statistical models [38], [39]. These models use transformer-based deep learning architectures trained on large language datasets, which typically contain billions of parameters [29], [40].

LLMs demonstrate powerful capabilities in natural language processing and text generation [41]. Additionally, because their training models encode a wide range of human behaviors, LLMs possess abilities similar to human environmental perception and decision-making, enabling them to solve complex reasoning and planning tasks [42], [43], [44], [45]. This capability enables them to “role-play” and simulate various human social behaviors.

As mentioned, Agent-based modeling (ABM) is one of the methods for researching complex human decision-making. However, traditional ABM has several drawbacks. These include excessively complicated model parameters [46], difficulty in handling comprehensive simulations of complex tasks and real-world problems [47], and dependence on straightforward "perception-action" loops for decision-making. Traditional ABM relies on these simple loops rather than intricate internal world models or sophisticated reasoning processes [48]. These limitations lead to discrepancies between simulation results and real situations.

Fortunately, LLM-based agents provide new ways to overcome these restrictions. Their special advantages include:

First, LLM-based agents are more capable of reasoning and making flexible decisions. Unlike traditional ABM with predefined rules, LLM agents can understand and process complex contextual information through natural language without explicit rules [44]. They can perform multi-step reasoning and make decisions that better align with human cognitive characteristics [49]. The Chain of Thought prompting technique is one typical example of LLMs' sophisticated thinking abilities. This technique breaks questions down into several successive intermediate steps to reach a final solution [50]. [51] further introduced the Tree of Thoughts framework. This framework allows LLMs to make thoughtful judgments by analyzing several lines of reasoning and conducting self-evaluation. By enabling agents to deal with more ambiguous and uncertain situations, this language model-based approach can improve the modeling of real-world decision-making processes.

Second, LLM-based agents show superior ability to integrate and transfer knowledge and data. LLMs have acquired extensive knowledge from pre-training, which enables them to comprehend and apply concepts from various fields. That helps agents achieve zero-shot or few-shot generalization by efficiently transferring information and drawing comparisons when confronted with novel situations [52], [53], [54]. Through Turing experiments, [55] have confirmed that LLMs can reproduce well-known studies in social psychology, psycholinguistics, and economics. LLMs can also adapt to changing settings and continually learn from new data [56], [57]. In particular, the combination of retrieval-augmented generation (RAG) allows for dynamic integration of user queries with relevant data from external knowledge bases. This helps to produce more precise and contextually relevant answers and exhibits strong knowledge manipulation skills in knowledge-intensive tasks [58]. These features greatly enhance agents' capacity to manage challenging real-world issues and bring simulations closer to actual situations.

Third, LLM-based agents are capable of complex interactions. On one hand, LLM-based agents can use natural language to communicate with their surroundings [59]. While tools broaden the agents' action space [44], [60], multimodal fusion models can process different kinds of environmental input [61]. This interaction is not restricted to text and predetermined rules. In addition to properly perceiving and interacting with their surroundings, LLM-based agents may also communicate with other agents[40], [49], [62]. This capability enables intricate negotiations, game theory applications, and collaboration in multi-agent systems. Therefore, this language-based interaction mode makes agent interactions more natural and diverse. It allows for more realistic simulation of complex interaction processes in human society. This approach has been used in many social simulation projects, including S3 to simulate the spread of information in social networks [63] and SocialAI School [64] to research and simulate developmental psychology. According to [65], LLM-based agents are able to replicate fundamental behavioral traits of human society, including consensus-building and conformity effects, which are consistent with theories in social psychology. MetaGPT, proposed by [66], achieves effective decomposition and collaborative completion of complex tasks by assigning specific roles to different agents. Similarly, [67] showed how multi-agent systems can use discourse to accomplish a variety of tasks. These advanced interaction capabilities enable LLM-based agents to exhibit collective intelligence and social phenomena.

Last but not least, LLM-based agents exhibit notable technical scalability. Training on a large dataset establishes fundamental zero-shot generalization capabilities. These agents can also be easily fine-tuned for other tasks to accommodate different application contexts [68], [69]. Using methods like prompt engineering and fine-tuning, researchers can easily customize the decision preferences and behavioral traits of agents. This significantly reduces the technological obstacles to creating complex agents and enables large-scale social simulation [54].

2.2.2 Framework and architecture of LLM-based agents

As a bottom-up research approach, agent-based model usually includes three basic components. Agents are individual entities within the system, each with unique attributes, behaviors, and decision-making mechanisms. Environment refers to the space in which agents operate and interact, as well as external factors that influence their behavior. Additionally, the interaction includes the mechanisms governing connections between agents and their environment, in addition to interactions among agents themselves [47]. Building upon these foundational concepts, many LLM-based agent architectures and frameworks typically incorporate several key architectural components that enable these enhanced capabilities.

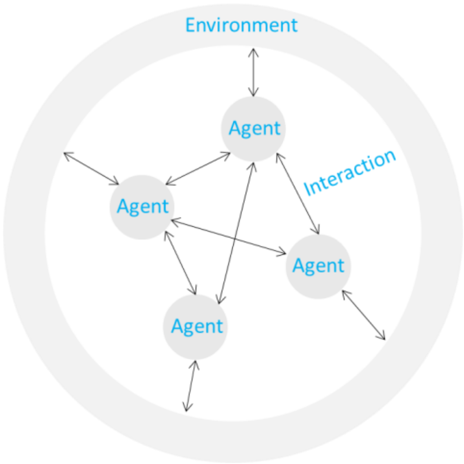

Figure 2-2 Basic components of Agent-based model

ReAct [45] is a well-known system that combines environmental interaction with the Chain-of-Thought reasoning power of LLMs. To accomplish complicated tasks, this framework uses a Think-Act-Observe loop. The agent first reasons about the current situation (Thought), then decides on and carries out a suitable action (Action), and finally receives feedback from the environment (Observation) to guide the subsequent reasoning step. This integrated method of action and reasoning makes it possible for agents to do multi-step tasks more efficiently.

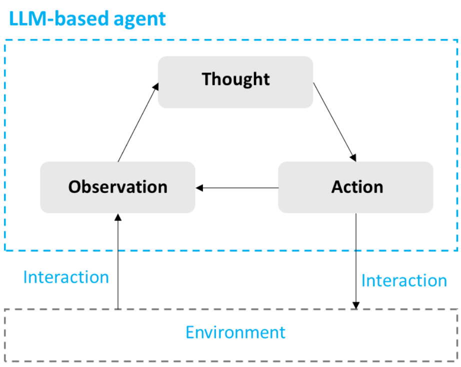

Figure 2-3 ReAct framework (edited by the author based on [45])

Another important framework is **Generative Agents**, proposed by [49]. This architecture is designed to generate realistic behaviors by simulating human cognitive processes. This process includes three core modules: memory retrieval, reflection and planning.

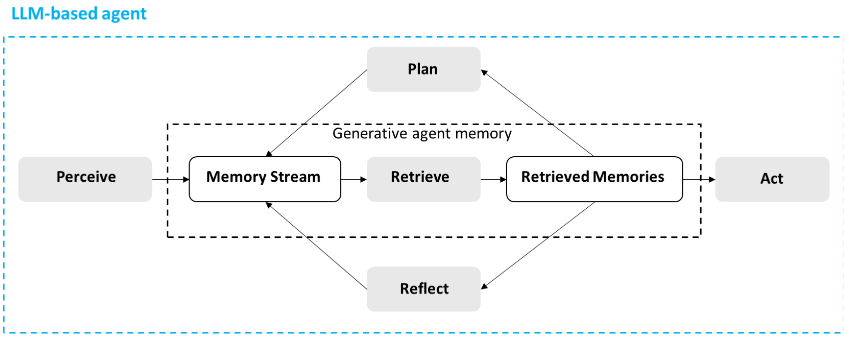

Figure 2-4 Generative agents framework (edited by the author, based on [49])

1) Retrieve: This module stores and retrieves the agent's experiences. It filters memories based on relevance, recency, and importance.
2) Reflect: This module synthesizes memories into higher-level reasoning. It helps the agent develop an understanding of itself and others.
3) Plan: This module creates tangible action plans based on these insights and the existing environment.

These three modules work together to produce a closed-loop system. In this system, actions create new memories that impact future reflection and planning in turn. Notably, this architecture has been used to create a virtual village with 25 agents that displayed social behaviors similar to those of humans.

[70] also proposed a unified framework built upon existing research to further enhance the capability of LLMs as agents in their systematic literature review. There are four main modules in this framework:

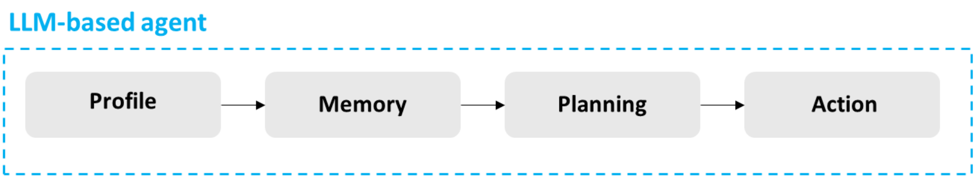

Figure 2-5 A unified LLM-based agent proposed by [70] (edited by the author)

1) Profile: This module determines the role of the agent and provides contextual guidance to other modules..
2) Memory: This module gives the agent the ability to remember previous actions and sense a changing environment.
3) Planning: This module aids in creating action plans for the future based on historical data and the present situation.
4) Action: This module is responsible for converting the agent's choices into tangible results.

Dynamic interactions exist between these modules. The Profile Module shapes the Action Module, and the Memory and Planning Modules are influenced by the Profile Module. This interconnectedness creates a cohesive and flexible agent framework. With this framework, LLM-based agents can acquire autonomous learning and evolutionary skills.

Similarly, [71] proposed another general architecture, consisting of three core components (see Figure 2-6). This structure enables agents to better perceive their surroundings, make informed decisions, and effectively execute tasks, making it applicable across various real-world scenarios.

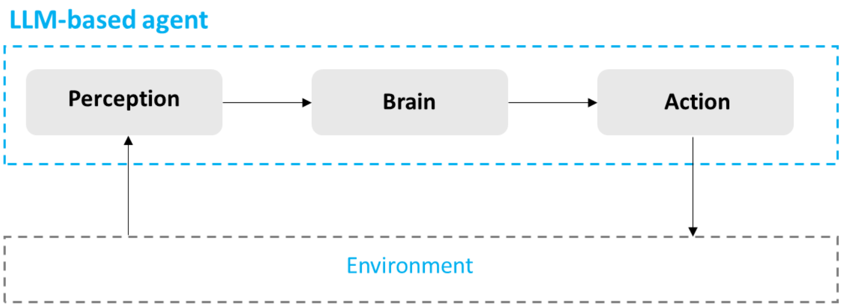

Figure 2-6 A unified LLM-based agent proposed by [71] (edited by the author)

1) Brain: This is the central component of the agent. It is powered by an LLM and is responsible for information processing, memory storage, thinking, planning, and decision-making.
2) Perception: This component enables a more thorough comprehension of the surroundings by extending the agent's sensory capacities beyond text to multimodal information, such as vision, sound, and touch.
3) Action: This component uses tools or specific acts to engage with and impact the outside world.

Although different architectures may vary in implementation and organization, several core modules are essential for building a well-functioning and highly capable LLM-based agent. These include:

(1) Profile Module

As the fundamental component of an LLM-based agent, the Profile Module is responsible for establishing and preserving its essential identification and traits. This module establishes important traits such as identity, personality, cognitive abilities, goals, and behavioral norms. Typical examples of these attributes include age, gender, occupation, psychological traits, and social network [49], [65]. These characteristic definitions form the agent's persona and serve as an important reference for other modules. By providing contextual support for other modules, it ensures behavioral consistency and predictability [72]. There are several approaches for generating these profiles, including manual configuration, LLM-based generation, and dataset alignment methods [70].

(2) Memory Module

An agent's ability to store, manage, and retrieve information from its surroundings depends heavily on the Memory Module. It enables the agent to remember prior experiences and apply them to future decision-making. According to [70], memory of LLM-based agents is often divided into two types: One is short-term memory. It mainly achieved by in-context learning. It stores immediate, task-relevant knowledge for a brief period within the agent's context window. However, context length restrictions are an inherent shortcoming of this approach. Another type is long-term memory, which provides the ability to efficiently retrieve past events and experiences as needed. It is usually stored in external vector databases. The integration of both types greatly improves the agent's capacity to participate in long-term reasoning and experience accumulation [73].

Memory retrieval can be optimized by some automated memory assessment procedures. For example, [49]introduces three important criteria to prioritize memory retrieval in their agent simulation: the memory's temporal proximity to the present circumstance (Recency), how important the memory is to the agent's goals (Importance) ,and the extent to which the memory relates to the current task (Relevance). This structured retrieval mechanism enables agents to effectively reuse past experiences, refine their problem-solving strategies, and adapt to new scenarios.

(3) Reasoning and Planning Module

The reasoning and planning module is the decision-making center of the agent system and handles sophisticated cognitive processing. This module first analyzes and reasons about the present state of affairs (e.g., the Thought phase in the ReAct framework), and then creates thorough task execution plans [45]. The module can dynamically modify planning in response to contextual changes and carry out high-level reflection based on memory (like the Reflection phase in Generative Agents) [49]. Furthermore, this module can decompose jobs into smaller, more manageable tasks, which increases the agent's effectiveness in solving complex issues. The chain-of-thought and the tree-of-thought we have mentioned above are examples of typical reasoning and planning procedures [50], [51].

Additionally, to improve the agent's capacity for planning and reasoning for certain tasks, there are common methods. For example, fine-tuning is to adjust model parameters by training on a specific task dataset. The handiest method is prompt engineering. And some apply mechanism engineering, which means introducing additional specialized modules [70].

(4) Action module:

The action module is the execution unit of the agent system. It usually collaborates closely with the memory and planning modules and uses a clearly defined action space to translate the language model's output into executable actions. Task completion, exploration, and engagement are typical action objectives [70].

In terms of task execution, LLMs are now capable of text output in multilingual environments [74]. Additionally, by integrating tool-use capabilities, this module can call a variety of other tools and APIs flexibly [44], [57]. This module also facilitates communication and collaboration among agents, establishing suitable social behaviors based on environmental awareness and information collection [47], [62], [65].

In addition to these four fundamental modules, LLM-based agents provide a significant architectural flexibility. This enables the development of more specialized modules to satisfy particular task needs. This modular extensibility, combined with their advanced reasoning and decision-making abilities, enables them to overcome some limitations of traditional ABM. This opens up new possibilities for studying and simulating complex systems by enabling them to interact with their surroundings and adapt to different conditions more skillfully.

2.3 Summary and Conceptual Framework

The above literature review examines the theoretical foundations, current research state, and methodological limitations in household PV adoption research. It highlights the necessity of integrating multiple theories and overcoming existing limits in modeling complex decision-making processes and multidimensional interactions. Additionally, this review explores the potential and implementation of LLM-based agents as decision simulators.

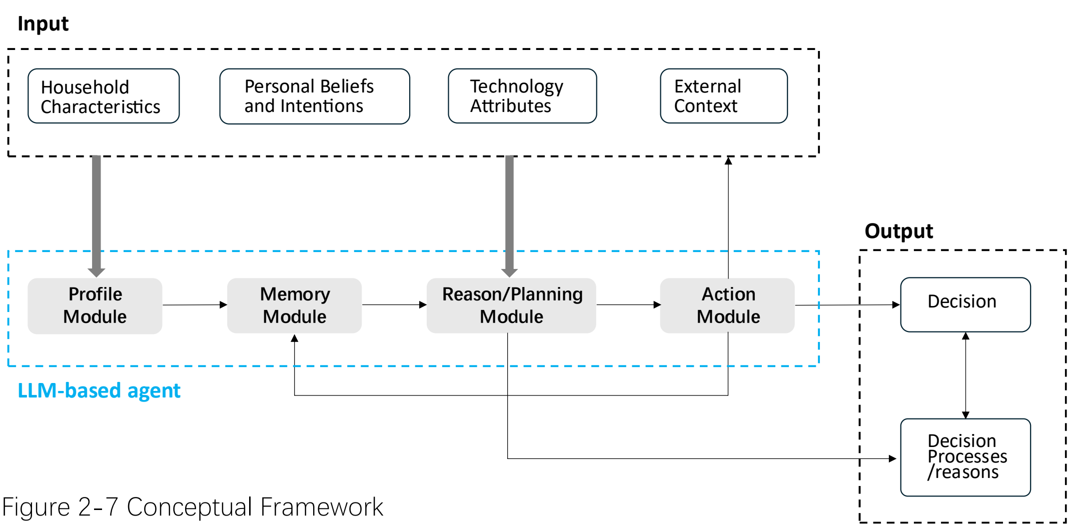

Figure 2-7 Conceptual Framework

Given that the main purpose of this paper is to explore the application of LLM-based agents in simulating household solar energy decisions, this paper will use the unified LLM agent framework mentioned above as the main theoretical framework. The goal is to explore new insights for promoting just adoption that this methodological innovation might bring.

This approach is supplemented by integrated decision-making theory, which provides a complementary theoretical perspective. It will guide the development of the input section, which will include household characteristics, personal beliefs, technical attributes, and other external context such as policy environment and peer effects. These inputs will provide the theoretical foundation for profile creation and reasoning logic. By doing this, we aim to ensure that the agent system acts as an interpretable decision-maker rather than a black-box predictor.

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Chapter 3 Methodology

This chapter introduces the research methods used to answer the three sub-research questions outlined earlier. These questions build upon each other progressively and each of them is associated with a particular analytical phase. Each phase includes specific data sources and analytical methods. This creates a mixed-methods approach that combines literature review, data analysis and LLM technology. The goal is to examine household solar panel adoption decisions from multiple perspectives.

3.1 Research Design

3.1.1 Phase One

In the preparatory phase, we conduct a literature review to answer the first research question by identifying key factors that influence urban residents' adoption of residential solar PV systems. We use Scopus as the primary search database, combining solar technology terms (e.g. Solar, PV, photovoltaic) with household-related terms (e.g. house, home, residential, dwelling) to examine relevant studies published between 2015 and 2023. We also employ multiple supplementary strategies to ensure more comprehensive literature coverage. These include expanding relevant literature through citation tracking, filling gaps by referencing existing review studies (such as [1]), and examining recent work by key researchers in this area.

Based on the research objectives, the inclusion criteria for the literature are defined by four key dimensions:

1) Technical focus: The study must involve rooftop solar or residential PV systems.
2) Behavioral perspective: The study must be related to adoption behavior, decision-making, or diffusion mechanisms.
3) Target subjects: The unit of analysis must be households, residential users, or neighborhoods.
4) Spatial scope: The study must be set in an urban context.

Additionally, we exclude certain types of studies: 1) research that treated specific factors (like peer influence or policy interventions) as the main dependent variable instead of explanatory factors; 2) studies that only examined specific local policy effects; 3) research focused on rural or remote areas; 4) purely technical or engineering studies.

After screening and verification, we finally include 65 empirical research articles. To ensure data consistency and comparability, we only retain explanatory variables that showed statistically significant effects in the studies. We organize these variables according to their directional relationship with adoption outcomes (positive, negative, or mixed). The factors are further classified using the four-dimensional theoretical framework proposed in Chapter 2. Detailed analysis and summary are presented in Chapter 4.

3.1.2 Phase Two

To answer the second research question, we focus on the development of an LLM-based agent model to simulate household solar adoption decisions in phase two. This phase includes the following key components:

1) Constructing basic attributes of individual agents: Based on real-world survey data, each household sample contains multiple structured information elements (such as income, housing type, energy bills). These factors are converted into natural language format as inputs for subsequent reasoning.
2) Building external environment information: We also collect relevant policy documents and programs about household solar adoption in Amsterdam. This provides context for specific case analysis and a more comprehensive understanding of external social conditions.
3) Neighborhood structure and temporal dynamics modeling: Beyond static adoption simulation, we add neighborhood network and yearly evolution mechanisms. This contributes to a multi-round simulation that shows how solar adoption spreads through neighborhoods.
4) Prompt template design and LLM integration: Using key factors from behavioral theory and research, we create well-structured prompt templates and configure optimal LLM parameters (such as temperature) to balance output diversity and consistency. The prompt guides the LLM to play as a household and make adoption decisions.
5) Validation and iterative optimization: Two external researchers are invited to manually review the model's decisions and reasoning to check if they logically make sense and show realistic variety. We further compare model outputs with real adoption data at the aggregate level to verify their reasonableness at the macro level.

Our method combines theoretical factors, real data, and LLM reasoning abilities to simulate complex social behaviors without supervised training. We develop the model in two steps: first building basic modules and prompts on static datasets, then expanding to multi-year, multi-agent models with neighborhood networks after validation. Chapter 5 will present the detailed implementation processes and validation results.

We implement the system using Python programming. For the LLM component, we select the "gpt-4o-mini" model to balance cost and performance considerations. Data security remains a priority throughout this process. To protect privacy, we remove identifying information from all data before using LLM APIs.

3.1.3 Phase Three

In this phase, we analyze the results from our LLM-based agent model over multiple years. This includes both adoption decisions and the reasoning behind them. We identify adoption trends as well as key barriers and motives to answer the third sub-research question.

We conduct the analysis in two parts. First, we analyze households' “yes (adopt)” or “no (not adopt)” decisions using adoption rates as indicators of group patterns. We examine adoption rates and growth trends across different years, while conducting comparative analysis based on various socioeconomic attributes, neighborhoods, and adopter versus non-adopter groups.

Second, we analyze the "reasoning" text that the model generates for each household each year. We use open coding and thematic analysis to identify the main decision factors behind adoption and rejection. These factors are further organized using the framework from Phase One. We calculate absolute and relative frequencies for each factor mentioned in the reasoning. The latter one is particularly important when different analysis groups contain varying sample sizes. We combine spatial, temporal, and household characteristics (such as income and housing type) to understand how different groups show different adoption patterns and trends over time.

Through these methods, this phase uses model agent behavior as the analysis object. This approach explores how individual decision-making connects with broader adoption trends. It provides theoretical support for identifying key adoption barriers and policy intervention potential.

3.2 Data

This study involves data from the following sources:

Table 3-1 Data category and source

Category	Year	Data type	Detail level	Source
Synthetic population of households in Amsterdam	2021	Synthetic data	Household-level	Derkenbaeva, Erkinai, 2023, "Synthetic population of households in Amsterdam", https://doi.org/10.1

				7026/SS/LUV9KW, DANS Data Station Social Sciences and Humanities, V1
WoON Dutch (Woononderzoek Nederland)	2021	Survey data	Household-level	Ministerie van Binnenlandse Zaken en Koninkrijksrelaties (BZK) and Centraal Bureau voor de Statistiek (CBS), 'Woononderzoek Nederland 2021 - woningmarktmodule- release 1.0'. DANS Data Station Social Sciences and Humanities, 2022. doi: 10.17026/dans-xaa-mrra.
Census information (Basisbestand Gebieden Amsterdam (BBGA))	2021, 2024	Statistical data	Neighborhood-level	Gemeente Amsterdam, "Basisbestand Gebieden Amsterdam (BBGA)," Onderzoek, Informatie en Statistiek (OIS), Accessed: Jun. 23, 2025. [Online]. Available: https://onderzoek.amsterdam.nl/dataset/basisbestand-gebieden-amsterdam-bbga
Basisregistratie Adressen en Gebouwen (BAG) data	2024	Spatial data	-	Kadaster, "Basisregistratie Adressen en Gebouwen (BAG)," Accessed: Jul. 17, 2023. [Online]. Available: https://bag.basisregistraties.overheid.nl/
Rooftop solar PV installation (Zonnepanelen - toename van aantal en vermogen)	2021, 2024	Spatial data	-	Gemeente Amsterdam, "Zonnepanelenkaart Amsterdam," Accessed: Jun. 23, 2025. [Online]. Available: https://maps.amsterdam.nl/zonnepanelen/

To overcome the limitations of small-sample household-level data, this study uses spatial microsimulation techniques [2] to generate a synthetic household population at the neighborhood (wijk) level. We follow a similar approach to [3], who applied Iterative Proportional Fitting (IPF) to generate synthetic data at the district level. In this study, we implement this method at a more detailed geographical level (wijk level) which enables a more thorough analysis of household data throughout Amsterdam.

The synthetic population is constructed by merging microdata from the WoON 2021 survey with marginal distributions from the Dutch Census and the BAG database. Both databases are publicly available. The main constraints include household composition, income level, area of dwelling livable space, and home ownership. The IPF approach repeatedly adjusts the starting sample weights to meet the constraints in each neighborhood. After IPF adjustment, we convert the continuous weights to integers to create a realistic, discrete synthetic population.

We validate our results by comparing the synthetic population distributions to the original constraints. We use Pearson's correlation coefficient and relative error (RE) as validation metrics. Results show that the synthetic population is appropriate for geographic analysis and highly consistent across all neighborhood areas.

Table 3-2 Summary of validation metrics for synthetic population across all zones

Constraint Type	Mean Pearson's r	Mean Pearson's p *	Mean RE
Household composition	0.999	2.61E-06	2.1%
House area	0.999	4.48E-06	1.2%
Income	0.998	2.09E-05	0.7%
Ownership	1.000	1.00E+00	0.4%

* All p-values are highly significant (< 0.001)

We use data in two phases during model development. The first phase focuses on static analysis and basic model setup, so we directly use WoON 2021 survey data to establish household characteristics and test initial decision simulations. The second phase uses the synthetic household dataset created through spatial microsimulation to support dynamic and network simulations at the neighborhood level. This dataset keeps the original population patterns while being scalable, allowing our model to run consistent simulations across different areas.

Additionally, we also include multiple macro-level background information to support external environment modeling in dynamic simulations. These include solar installation costs, electricity price, and national and local incentive policies (such as subsidy programs and regulatory adjustments). These data sources primarily include Statistics Netherlands (CBS), Milieucentraal.nl, and policy documents published by the Amsterdam municipal government. Detailed data information is provided in Appendix A.

3.3 Acknowledgement of AI Use

Generative AI is an essential part of the technique and the research itself since this study focuses on investigating and deploying LLM-based agents for decision simulation in solar adoption research. Additionally, generative AI will be only used for spell-checking, grammar correction, and code review. All AI applications in this study adhere to Wageningen University's guidelines on the Use of Generative Artificial Intelligence. The detailed statement with examples can be found in Appendix E.

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Chapter 4 Factors influencing household solar PV adoption

As Li [1] pointed out, research on distributed PV system has become increasingly active since 2015, with technical-economic analysis and application decision analysis being the most prominent research areas. Although numerous studies and review articles have focused on factors influencing household-level decision-making, existing surveys have limitations. Most surveys concentrate on specific dimensions or limit their attention to other factors by starting from particular theoretical frameworks.

For example, Alipour et al. [2] review over 170 studies focusing on residential solar adoption behavior and identified more than 330 predictor variables. These variables are categorized into three dimensions: personal (attitudes), social, and informational (knowledge). This comprises 20 categories as shown in Figure 4-1 below. However, these variables only focus on internal factors related to personal attitudes and conditions while neglecting the impacts of external environmental changes.

Similarly, other studies have focused on narrow aspects. Ghosh and Satya Prasad [3] primarily focused on the influence of environmental awareness and knowledge; Konzen et al. [4] summarized the relationship between PV adoption and income/wealth; and Ashraf Fauzi et al. [5] mainly reviewed factors related to solar system performance based on Rogers' Diffusion of Innovations Theory.

This lack of systematic understanding of influencing factors presents the first challenge we face in building an LLM-based agent. Therefore, we conducted a review analysis of factors affecting household photovoltaic adoption decisions. This chapter presents the results of this analysis. It answers our first research question: What (internal and external) factors influence household decisions to adopt solar PV systems?

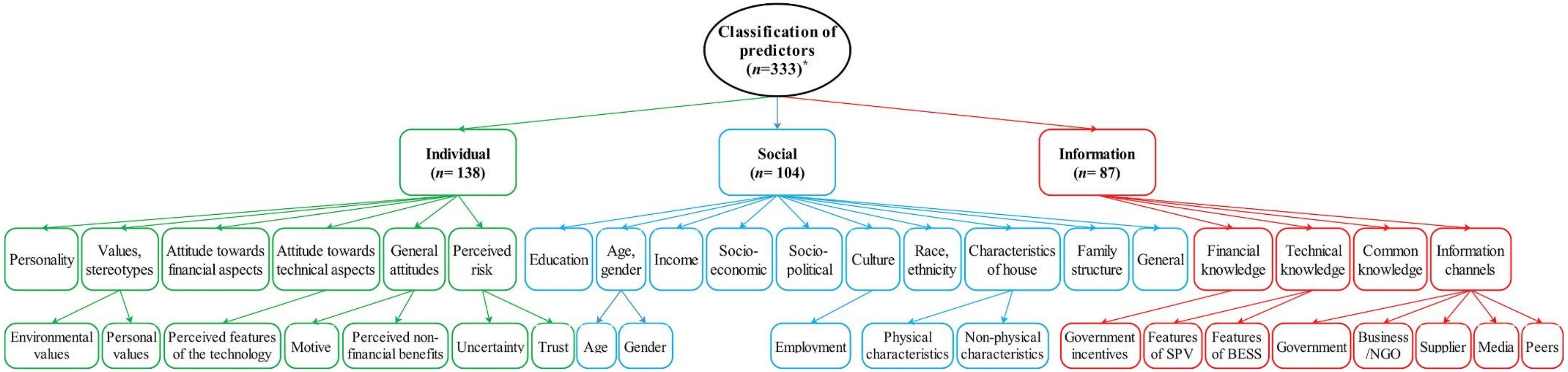

Figure 4-1 Alipour et al.'s predictors of rooftop solar PV adoption behavior by household, which only focus on internal factors. (source: [2])

4.1 Overview

This analysis includes 65 empirical papers published between 2015 and 2023 (see Appendix B). These papers examine various factors impacting residential rooftop solar system adoption decisions in urban areas. The selection process can be found in Chapter 3.

The included literature primarily focuses on developed countries such as the United States and Europe, with a smaller portion covering developing countries including China, India, and Pakistan. These studies span analysis at national, regional, and specific city levels, with analytical units generally classified into four categories: Individual/Household level, Neighborhood/Postcode level, Census tract level, and County level. Despite differences in specific categorization among nations, they can typically be grouped using this hierarchical structure in Figure 4-2.

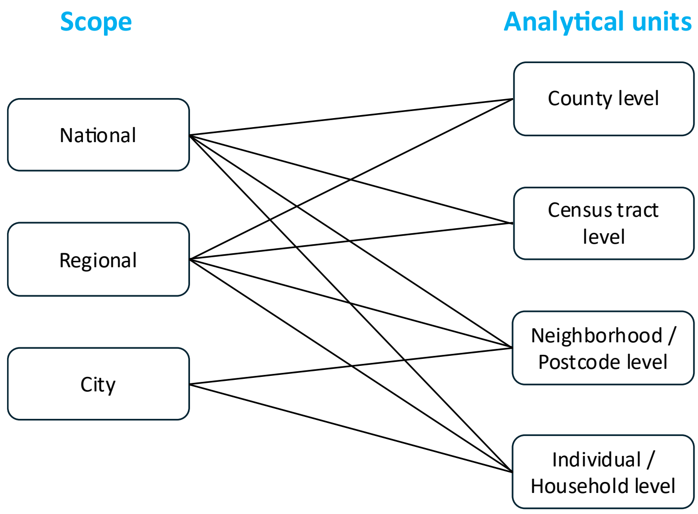

Figure 4-2 Research scope and analytical units

We conduct an analysis of the factors influencing household rooftop solar PV adoption mentioned in the literature above. We include only statistically significant factors, categorizing them according to their relationship with solar adoption as positively correlated, negatively correlated, or having mixed relationships (such as U-shaped relationships).

Initial synthesis reveals that despite differences in geographical scope, data sources, and research methodologies across studies, certain influencing factors demonstrate consistent statistical significance in most research. For example, financial variables related to installing household solar systems (such as initial installation costs [6], [7], [8], [9], [10], [11], [12], [13], [14], [15], [16], [17], [18], [19] show strong effects. External contexts represented by policy incentives [6], [8], [9], [20], [21], [22], [23] and peer effects [9], [10], [20], [21], [24], [25], [26], [27] also demonstrate significant influence. Additionally, household and individual economic conditions [9], [11], [16], [17], [18], [22], [23] have been frequently confirmed in multiple studies to have significant impacts on solar adoption behavior.

Meanwhile, we also observe that studies at different analytical units show certain differences in variable selection and significance. Individual-level studies [9], [19], [28] more commonly focus on beliefs, attitudes, and income among other micro-characteristics, while regional-level studies [24], [29], [30] tend to emphasize the importance of external variables such as solar radiation resources and policy environments.

To further clarify the manifestation paths and interrelationships of these factors across different studies, we have categorized the variables influencing household solar system adoption into four dimensions based on the conceptual framework proposed in Chapter 2. The four dimensions are: **Technology Attributes** (characteristics of the technology itself, such as installation costs and efficiency), **Household/Individual Characteristics** (objective features at the individual level, such as household income, education level, and home ownership), **Personal Beliefs and Intentions** (individual attitudes toward the technology, values, and behavioral motivations), and **External Context** (external institutional and social conditions including physical environment, policy environment, and social networks). The following sections will systematically review each category of factors according to this classification framework. We will incorporate the tallying results of variables across different analytical levels.

4.2 Key Factors per dimension

4.2.1 Technology Attributes

According to existing literature, the technological attributes influencing household rooftop solar system adoption can be broadly categorized into four aspects. These are cost, benefits, technical functionality and performance, and user experience and perception, as shown in Table 4-1 below.

Table 4-1 Technology Attributes Factors

Category	Factors	Descriptive variables	Positive relationship	Negative relationship	Mixed relationship
Cost	Cost	Initial cost/Investment/Price		[6], [7], [8], [9], [10], [11], [12], [13], [14], [15], [16], [17], [18], [19], [31], [32]	
	Affordability	Affordability	[9], [23], [26]		
	Payback period	Expected payback period/pay-back time		[9], [16], [22], [33]	
	Offer	Received an offer too good to refuse	[34]		
Benefits	Economic benefits	Expected financial returns / Return on the investment	[12], [26], [35], [36]		
	Environmental benefits	Environmental benefits	[13], [22], [35]		
	General benefits	Relative advantage / expected benefits / perceived personal benefits	[8], [37], [38]		
Functionality and Performance	Efficiency	Efficiency	[11]		
	Installation	Ease of installation/Installation quality	[39]		
	Maintenance	Maintenance / Concerns about operations and maintenance		[12], [32], [40]	
	Difficulty of using	Difficulty of using all applications at the same time/Difficulty of using		[13]	
	Visual influence	Visual representation	-	[11]	
User Experience and Perception	Trialability	Trialability	[16], [37]		
	Efforts	Efforts	-	[10]	
	Risks	Risks	-	[10]	

Cost is one of the most critical factors influencing household PV system adoption behavior. Related variables frequently appear in the literature as “initial cost,” “investment,” “installation price,” “affordability.” Some studies use “expected payback period” or “payback time” as indirect measurements of cost. These variables collectively reflect the economic burden faced by users during the installation phase. Almost all studies involving these variables have found a significant negative correlation between cost and PV adoption. This means that higher costs and longer payback periods reduce users’ willingness to adopt. On the other hand, Bondio et al. ’s result [34] shows that an “irresistible price offer” had the strongest positive influence on people’s adoption decisions.

In contrast to cost, studies investigating users’ subjective expectations of potential economic **returns** from PV systems generally found positive correlations. Some literature also uses “perceived personal benefits” or “relative advantage” as a more comprehensive description. A few studies further incorporate environmental benefits into the scope of returns. Although their impact is less important compared to financial returns, they still act as a positive push in samples with stronger environmental awareness.

The third group of factors focuses on the **technical performance** of the PV system during use. High efficiency is typically considered to provide faster payback, thus positively correlating with adoption. System maintenance and operational burden are also important influencing factors. Concerns about these issues and repair needs negatively impact adoption [12]. Furthermore, some studies have examined installation and usage difficulties [13]. If users perceive system installation as challenging or difficult to coordinate with existing facilities, their willingness to adopt may decrease.

Users' perception of PV system’s attributes also impacts their desire to adopt. One key aspect is trialability, which allows users to assess system performance before installation. This reduces users’ uncertainty and thereby favorably influencing adoption behavior [16], [37]. This aligns with relevant propositions in Diffusion of Innovations Theory [41].

4.2.2 Individual and Household Characteristics

Characteristics at the individual and household levels have been widely employed as variables in previous studies. These are significant factors that impact adoption decisions. These are further divided into several categories, as indicated in Table 4-2 below.

Table 4-2 Individual and Household Characteristics Factors

Category	Factors	Descriptive variables	Positive relationship	Negative relationship	Mixed relationship
Demographic Characteristics	Age	Age	[11], [22], [32], [34], [42], [43], [44], [45]	[9], [10], [17], [18], [28], [29], [37], [46], [47], [48], [49]	[16], [50]
	Gender	Gender (male)	[18], [32], [37], [42], [49], [51], [52], [53]	[28], [50]	
	Marital status	Marital status		[50]	
	Education	Education	[11], [16], [17], [22], [25], [27], [28], [30], [35], [36], [38], [44], [45], [48], [50], [51], [53], [54], [55], [56], [57]	[31], [32], [43]	
		Literate	[49]		
	Ethnicity	Ethnicity/ Race / Immigration (foreigner/black/non-white/minorities)		[31], [42], [49], [56], [57], [58]	
	Language	Linguistic isolation		[55]	
		Language proficiency	[56]		
		Native language	[59]		
	Household structure	Household size	[27], [28], [42], [43], [45], [50], [58], [60], [61]	[11], [25]	
		Number of children	[18], [51]	[61]	
Economic & Financial Status	Income & Wealth	Income	[9], [11], [16], [17], [18], [22], [23], [24], [25], [27], [30], [31], [36], [38], [42], [46], [48], [49], [55], [56], [57], [60], [62], [63]	[34], [35], [45], [50]	
		Savings	[7], [9], [52]		
		Wealth	[29], [42], [44], [51], [52], [61]		
		Private pensions	[61]		
		Poverty	[57]	[55]	

		Economic comfort	[53]		
	Credit and Burden	Housing burden		[55]	
		Mortgages	[61]		
		Financial stability	[21]		
		Number of credit cards	[61]		
	Employment	Percentage of population receiving income	[60]		
		Number of employed persons		[61]	
		Unemployment		[36], [64]	
		Retirement	[34], [54]		
		Employment type (public sector)	[42]		
Housing Characteristics	Ownership	Home ownership	[9], [11], [24], [25], [28], [31], [42], [43], [46], [50], [53], [57], [58], [59], [60], [61]		
		Renter rate		[64]	
	Type	Housing type (detached house/single-family units)	[11], [25], [31], [50], [57], [58], [60]		
		Housing type (apartment/high-rise)		[9], [18], [42], [43], [59], [61], [63]	
		Housing storey	[54]		
	Size	Housing area	[23], [27], [32], [42], [43], [53], [54]		
		Total building footprint	[45]		
		Number of bathrooms	[34], [49]		
		Number of bedrooms	[61]		
		Number of housing units		[28], [49]	

	Rooftop	Roof quality	[42]		
		Roof space	[46], [49]		
		Rooftop potential	[56]		
	Value	Home value	[23], [29], [42], [56], [57], [58], [59], [62], [65]		
		Land value		[33]	
		Property value	[60]		
	Age	House age	[56]	[32], [42], [53], [58], [60]	
		Years of living in current house		[61]	
	Quality	Housing quality	[54]		
		Energy efficiency status of the house (double glazing)	[42]		
		Energy efficiency status of the house (roof insulation)		[42]	
Energy consumption Pattern	Energy consumption	Electricity consumption	[30], [61], [62]	[60]	
		Household energy consumption	[38]		
Future plan	Expected living time	Expected living time	[27]		
	Retirement planning	Retirement planning	[12], [27]		

Demographic characteristics are frequently used as critical control variables in research. Among these, age and education are the most commonly discussed variables.

While several studies reveal statistically significant connections between **age** and solar energy adoption, there is little agreement on the direction of this relationship. Positive and negative correlations are found in nearly equal measures. Additionally, some studies [16], [50] have identified U-shaped or inverted U-shaped relationships between age and adoption probability, implying that middle-aged people are more or less likely to adopt than any other group. As a result, it is difficult to conclude a solid link between age and adoption preferences, especially when other characteristics are taken into account.

In contrast, most studies have found a positive influence of **education level** on adoption decisions. Only a few studies indicate a negative relationship. One possible explanation for these negative findings is that neighborhoods with a higher percentage of university or higher-educated populations frequently have more institutional buildings and apartments [62]. They are primarily occupied by students or temporary researchers who are unlikely to adopt solar energy systems.

Household structure and size are also seen to be crucial components in decision-making. Bigger family sizes often indicate a higher possibility of adoption, potentially due to higher power use. Furthermore, multiple studies have identified correlations between male **gender** and adoption tendencies [37], [42], [51], as well as the disadvantaged position of **racial minority** groups in solar energy adoption [42], [49], [56].

Economic and Financial Status is another widely studied cluster of variables. The majority of studies show substantial positive relationships between income and adoption rates. However, a few studies [61] show that wealth explains a household's economic capability better than income. These findings are relevant to the comparatively high investment costs associated with residential solar PV installations [23].

Ownership is seen as the most influential housing characteristic, as tenants often lack decision-making capacity [29]. Furthermore, **housing type** has a significant impact on adoption. Single-family or detached homes often having suitable roof conditions for solar installation, as opposed to multi-story residences and flats [60]. Other noteworthy contributing factors are **housing value and housing age**, both of which may be explained in terms of homeowners' willingness to invest [42]. Some studies [59] also use house value as an indicator of household economic status.

Considerations such as **energy consumption** and **future residential** or **retirement plans** have also been shown to influence the decision-making process for residential solar PV installations.

4.2.3 Personal Beliefs and Intentions

Beyond household characteristics and settings, human attitudes and motivations have a significant effect on solar adoption decisions. This is evidenced by theories like Theory of Planned Behavior (TPB) [66] and the Value-Belief-Norm Theory (VBN) [67]. These factors are shown in Table 4-3.

An individual's **knowledge** influences their decision-making. This includes an understanding of solar PV panels, awareness of environmental changes, and familiarity with related legislation, subsidies, and costs. According to research [15], [26], [47], [68] higher levels of knowledge are associated with an increased chance of adoption.
Environmental awareness is considered an important facilitating factor, particularly among early adopters when PV systems were more expensive [39]. Additionally, **attitudes toward technology** and **political beliefs** impact adoption: individuals and households who are more accepting of new technologies, lean politically left, and support government and solar energy organizations are more likely to use residential solar PV technology [45], [52], [69].

Motivation is a significant facilitator. Economic benefits, incentives, and reaching energy self-sufficiency being the most important drivers for many users [9], [10], [12], [39]. Other motivators include intentions to improve housing systems [68], investment reasons [32], and pressure from societal standards [11]. Notably, the time and habits of the decision-making process both impact choice results [11].

Table 4-3 Personal Beliefs and Intentions Factors

Category	Factors	Descriptive variables	Positive relationship	Negative relationship	Mixed relationship
Knowledge	Objective Knowledge	Environmental knowledge / Knowledge of technology / Knowledge and information about green energy / Knowledge of renewable energies and its outcome / Knowledge of grants and costs / Knowledge about PV policy / Factual knowledge / Expert	[15], [17], [26], [28], [39], [40], [48], [68], [70]	[32], [47]	
	Perceived Knowledge	Aware of the possibility / Knowledgeable or confident with solar / Subjective knowledge	[19], [47]		
		Uncertainty of the suitability		[19]	
Environmental Values	Environmental Concern and Awareness	Climate change concerns / Ecological attitude / Environmental awareness / Environmental responsibility / Environmental attitude / Pro-environmental attitudes / Sustainable minded	[11], [16], [19], [21], [24], [28], [29], [32], [36], [40], [42], [48], [70]		
	Pro-Environmental Behavior	Sustainable activity / Green activities (recycling regularly) / Ecological lifestyle	[29], [48], [69]		
Technology Attitudes	Openness to Innovation	Interest in technology / Interest in testing / Novelty seeking / Innovativeness / Motivations to use a green technology	[16], [19], [28], [32], [35], [69], [71]		
	Attitudes Toward Solar PV Technology	Attitude toward rooftop PV installation / Opinion on visual appeal of solar panels /	[52], [69]		
		Concerns about the technology / Concerns about the long-term risk / System is ugly		[19], [32], [71]	
Political & Institutional Attitudes	Political Identity	Democratic party votes / Groen Links voters	[27], [29], [45]		
		Conservative /		[47]	
	Policy Support	Pro-government sentiment / Support PV market	[19], [46]		
	Institutional Trust	Trust in institutions / Trust in PV Industry / Trust in local	[15], [37], [44], [72]		

		contractors/ Trust on solar panel providers			
Financial Considerations	Economic Benefit Motivation	Financial considerations / Saving on electricity bill / Reducing electricity tariffs / Getting reasonable energy price / Saving on energy cost	[9], [10], [11], [13], [16], [19], [22], [26], [27], [35], [39], [71]		
	Cost Sensitivity	Perceived affordability /	[26]		
		Concerns about costs / Price is important		[32], [37]	
	Financial Support Access	Access to subsidies	[35]		
Energy Independence	Energy Need	Demand for electricity	[25]		
	Self-Reliance	Autarky / Self-reliance / Decreased dependence / Go off-grid / Independence from electricity retailer / Energy reliability /Energy independence	[9], [10], [12], [16], [19], [39], [40]		
Home Improvement motivation	System Upgrades	Energy efficiency upgrade / Co-adoption (other energy product)	[12], [32], [68]		
		Satisfied with the current system		[19]	
	Property Value Investment	Increase resale value / Impacts on home value	[27], [32]		
Social Aspects	Normative Expectations	Traditional norms / Necessity of rules / Personal norms / Pro-environmental norms / Personal norms about environmental issues	[11], [53], [71]		
	Social Motivation	Social curiosity / Symbolic (Set an example for others) / Psychological warm glow benefit / Social status benefit expectation	[10], [16], [37], [69]		
	Decision-Making Dynamics	Independence of taking decisions / Engagement / Independent judgment making	[11], [47], [71]		
		Time for making decisions		[11]	

4.2.4 External Context

Research shows that external circumstances beyond the household and individuals have an influence on whether families install solar PV systems (see Table 4-4).

Policy support and subsidies provide a favorable context for promoting residential solar PV systems [6], [8], [20]. They help households overcome high initial investment costs and make adoption decisions easier. Conversely, some studies mention that regulatory inadequacies and bureaucratic complexities discourage adoption [10], [16].

Available information is also important. This includes details about solar products, market circumstances, and policy situations [6], [9], [12]. Additionally, sources of awareness, such as media publicity and manufacturer marketing, have been proven to positively affect public knowledge and acceptability [55].

Neighborhood effects and **peer support** are among the most significant influencing factors mentioned in most articles. According to research [40], the appearance of technology is not especially important. Peer impacts usually occur through verbal communication, but if the source is recognized, both visual and verbal aspects might influence adoption likelihood.

Electricity market circumstances affect people's decisions as well. When **electricity prices** are high or increase significantly over a short period, people are more likely to adopt solar systems [12], [32], [34]. This relates to the financial motivations and desire for energy self-sufficiency mentioned previously [12].

Finally, **physical environments** limit solar potential and installation conditions. On one hand, geographic conditions, especially available solar radiation, form the foundation for determining PV system’s generation efficiency and payback periods [49], [50], [56], [59]. On the other hand, research finds that urbanization levels and population density tend to negatively impact PV adoption [36], [45], [50], [57]. This is because higher-density areas typically feature multi-story and high-rise residences, where fewer residents have access to rooftop space.

Table 4-4 External Context Factors

Category	Factors	Descriptive variables	Positive relationship	Negative relationship	Mixed relationship
Policy & Government Support	Incentive	Government subsidy / Policy incentives / Financial incentives / Governmental support	[6], [8], [9], [14], [15], [16], [17], [20], [21], [22], [23], [29], [30], [35], [36], [39], [40], [42], [63], [69], [73]		
	Regulation	Administrative process / Administrative procedures / Lack of regulations /		[10], [16]	
		Understandable Net-billing	[39]		
Information & Communication Context	Information Availability	Information Availability / Information context / Objective information / Available information and knowledge of solar PV system in the market / Certainty around FiT	[6], [9], [12], [16], [17], [38], [40], [44]		
	Communication Channels	Communication network / Media / Marketing / Sources of awareness	[9], [12], [22], [27], [38], [44]		
Social & Community Factors	Neighborhood Effects	Neighborhood effects / Peer effects / Social influence / Social support / Number of installers	[9], [10], [12], [15], [16], [20], [21], [23], [24], [25], [26], [27], [29], [31], [32], [33], [36], [37], [44], [47], [48], [52], [62], [64], [70], [72], [73], [74]		
	Local Actors	Local entrepreneur / Local organizations promoting PV	[21], [74]		
	Installer & Technical Support	Installers / PV company / Reliable technicians / Qualification of installer	[12], [13], [16], [30]		
Market & Economic Context	Electricity Prices	Electricity retail price / Recent increase in electricity rates / Electricity prices	[12], [15], [21], [27], [29], [32], [34], [44], [61]	[31]	

		increase / Residential electricity price			
	Economic Context	GPA / Market maturity / Dispersion of income	[30], [39], [42]		
		Gini		[57]	
Environmental Factors	Geographical Potential	Solar radiation / Insolation / Solar resource / Solar resource potential / Rooftop solar PV potential / PV Potential (radiation, slope, orientation) /	[22], [24], [25], [29], [33], [36], [49], [50], [56], [59], [62], [65]		
		Tree-cover ratio		[65]	
	Environmental problem	Pollution levels / Environmental problems / Environmental and pollution burden indicators		[25], [55]	
	Urbanization	Urbanization / Address density / Population density / House density / Household density / Population density / density / Amount of households / Number of housing units / Ratio of new residential building units / Construction of new buildings	[30], [47], [60]	[25], [29], [36], [42], [45], [50], [57], [64]	[49]

4.3 Summary and discussion

Figure 4-3 shows the most important and most frequently mentioned factors in each dimension.

Technology Attributes	Individual (household) Characteristics	Personal Beliefs and Intentions	External Context
Cost	Age	Knowledge	Policy Incentive
Payback period	Gender	Environmental awareness	Information
Economic benefits	Education	Technology Attitudes	Neighborhood Effects
	Ethnicity	Benefit Motivation	Electricity Prices
	Household size	Energy Independence Motivation	Geographical Potential
	Income		Urbanization
	Wealth		
	Home ownership		
	Housing type		
	Housing size		
	Home value		
	House age		
	Electricity consumption		

Figure 4-3 The most frequently mentioned factors in each dimension

It is worth noting that although most influencing factors have relatively clear directionality, there may be strong collinearity between different factors. Statistical correlations cannot truly reflect the complexity of reality. This makes it difficult to simply explain households' comprehensive decision considerations through regression. A typical case is where Gao & Zhou [31] found a negative correlation between education level and solar energy adoption. This phenomenon may partly stem from objective limitations that prevent students and temporary researchers from adopting solar equipment. More critically, education has a positive correlation with income. Therefore, when income variables are controlled in regression models, the impact of educational factors on solar adoption turns negative. This demonstrates the complex interactions between variables.

This complexity of influence is further demonstrated across different spatial conditions and combined scenarios. Using machine learning techniques, Lan et al. [75] have shown that several factors limit the explanatory power of income for solar adoption. For example, in areas with both high population density and high income, many apartments and residential units are unable to install PV systems due to limited roof space. Furthermore, in areas with moderate population density, the situation becomes more complex. Various socioeconomic factors interact and constrain one another, collectively influencing PV technology adoption outcomes.

Additionally, the relative importance of the different decision-making criteria varies greatly depending on the stage of technology adoption. According to Rai et al. [12], higher income and education levels are more significant in the early stages of residential PV adoption. This may be related to the higher costs of acquiring information and making investment. Similarly, Walters et al. [39] discovered that the initial wave of adopters generally acquired solar panels for environmental concerns, whereas the second generation prioritized financial considerations. This indicates that the importance of influencing factors dynamically changes with technology diffusion stages.

This complexity highlights the need for reinterpretations of these dynamics. Traditional models frequently fail to adequately capture the dynamic character and intricate interconnections of household decision-making. Therefore, more innovative approaches are required. The information acquired in this chapter will be used in the following chapter to develop an LLM-based agent model that simulates household decisions about solar energy adoption.

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Chapter 5 Model Development

This chapter details the development process of an LLM-based agent model designed to simulate a household's decision-making regarding solar PV adoption. It aims to answer the second research question: To what extent can LLM-based agents effectively simulate household decision-making processes for solar PV adoption?

5.1 Overview

As discussed in Chapter 2, LLM-based agents typically comprise several key modules: profile, memory, reasoning and action module. Input is generally presented by natural language prompts, enabling LLMs to simulate decision-making by synthesizing multidimensional information. In the previous chapter, we also identified four key dimensions of factors influencing household solar PV adoption based on the literature: household/individual characteristics, personal beliefs, external context, and technical attributes. These dimensions provide the basis for our LLM-based agent model design.

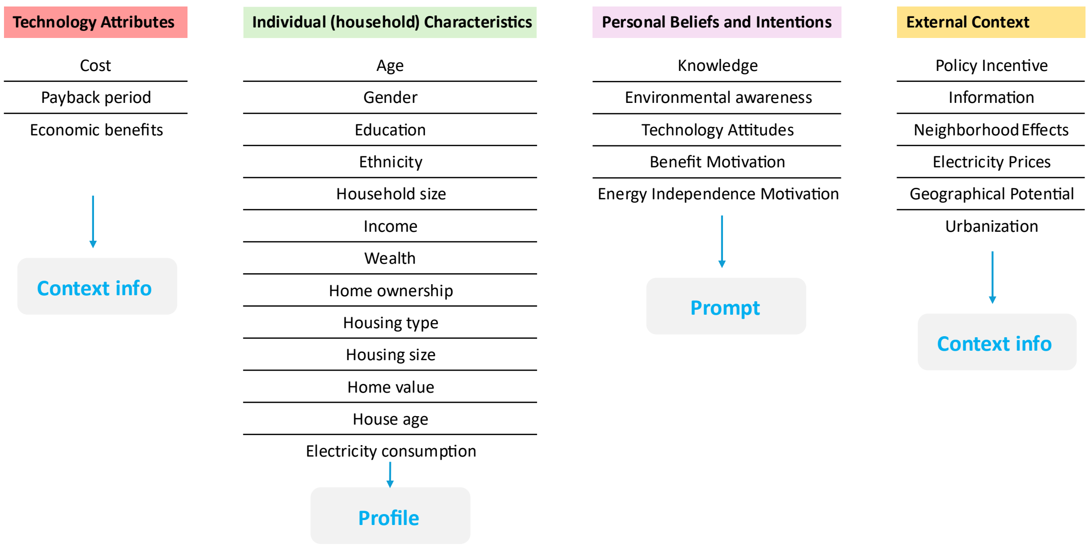

Figure 5-1 From factors to variables (Based on the conclusion of Chapter 4)

Specifically, individual and household characteristics serve as key variables in the profile module, providing the household's basic information. External context and technical attributes are added to prompts as supplemental information, enhancing the model's contextual comprehension. Due to the absence of structured indicators that explicitly reflect personal beliefs in the dataset, such beliefs are not introduced as distinct variables. Instead, they are implicitly addressed through prompt instructions that encourage the LLM to account for value heterogeneity in its reasoning process. It is worth noting that real-world situations involve complexities such as decision-making authority issues for tenants and diverse collective decision-making processes in housing associations. Given these complexities and time constraints, this research focuses exclusively on the most basic case of homeowners.

To systematically develop and validate the applicability of the LLM-based agent (hereafter referred to as PVAgent), model development in our research has two phases as shown in Figure 5-2. The first phase focuses on modeling individual adoption decisions based on static variables in a single round. During this phase, the LLMs help the household agent to determine whether they would adopt solar PV technology in a specific year. This decision is based on households' characteristics (such as age, income, and housing conditions) and the relevant static social and policy environment (including electricity prices and adoption rates). This phase aims to validate the LLM's capability for simulating individual decisions and create an initial prompt architecture. The second phase expands on the first by including temporal dynamics and neighborhood structures, progressing to a multi-agent system. This phase involves creating community networks, modifying external environments on a yearly basis, and modeling agent interaction and diffusion processes. These steps enable long-term dynamic simulation of solar PV adoption behaviors. This simulation allows us to investigate decision patterns of various household types under the influence of neighborhood effects and contextual change.

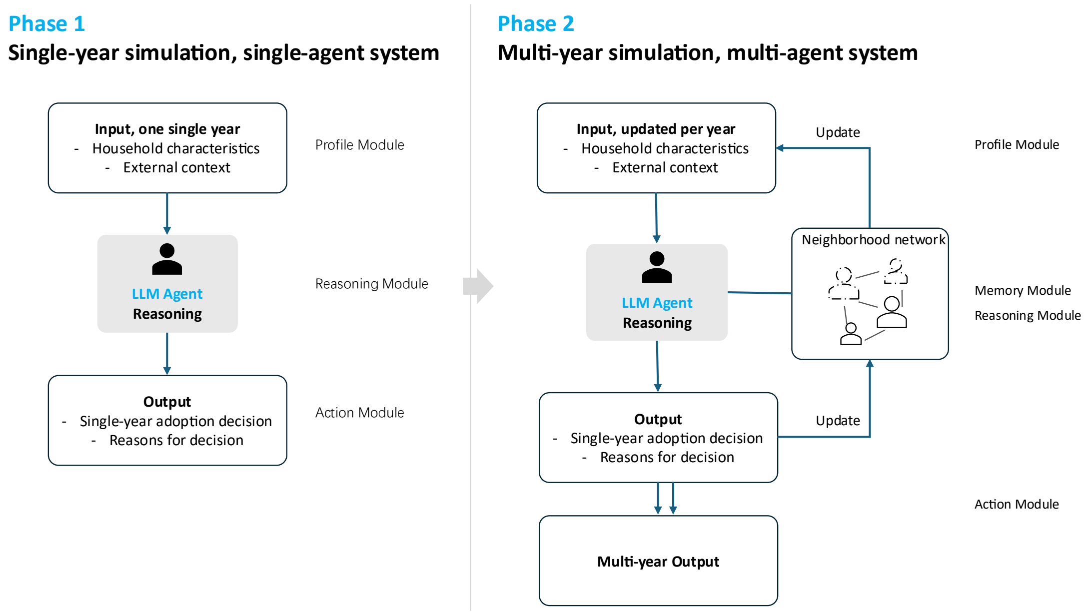

Figure 5-2 Two-phase development of PVAgent

5.2 Phase 1: Static Decision Modeling with LLM Agents

The purpose of this phase is to verify whether an LLM can accurately simulate the decision-making for solar PV adoption based on household characteristics and the external environment in a specific year. We employ a fundamental static scenario, excluding temporal dynamics and neighborhood interactions and focusing solely on the individual agent's judgment process under given conditions. Consequently, the memory module is temporarily excluded from the model at this stage. Due to data availability, we use 2021 as the contextual year for this phase, based on the WoON dataset [1].

5.2.1 Input Data

As mentioned, the input primarily includes basic household characteristics and external information. Considering the important factors summarized in Chapter 4 and data availability, we extract basic household characteristics data from our prepared dataset to build the profile. These variables include age, education level, income, wealth, household size, housing type, building livable area, construction year, and energy consumption. It should be noted that despite their possible relevance, gender and race are not included because the data is not available. Additionally, the level of neighborhood connection is incorporated as a feature reflecting the intensity of peer effects. Table 5-1 provides a complete overview of variables used in profile construction, including their categories and whether they are static or dynamic in the modeling process.

Table 5-1 Overview of variables used in household profile (Data source: [1])

Variable	Description	Categories/Range	Phase 1 Role	Phase 2 Role
Age	Age of household head	17-24/25-34/35-44/45-54/55-64/65-74/75 and older	Static	Dynamic
Education Level	Highest education level	Low/Medium/High	Static	Static
Income	Annual household income	Continuous (€)	Static	Dynamic
Wealth	Household wealth	Continuous (€)	Static	Dynamic
Household Size	Number of household members	1 person/2 people/3 and more	Static	Static
Housing Type	Type of dwelling	Non-apartment/Apartment	Static	Static

Variable	Description	Categories/Range	Phase 1 Role	Phase 2 Role
Building Livable Area	Floor area of the dwelling	Continuous (m²)	Static	Static
Construction Year	Year house was built	Continuous (year)	Static	Dynamic
Energy Consumption	Annual energy consumption	Continuous (kWh)	Static	Dynamic
Neighborhood Connection	Agreement with "I have a lot of contact with neighborhood residents"	Totally disagree/Disagree/neither agree nor disagree/agree/totally agree	Static	Static

The data extraction and profile generation process are fully automated through a Python-based pipeline. The system reads each household record from the dataset and automatically converts numerical and categorical values into natural language descriptions to construct individualized agent profiles. The following paragraph shows an example of a profile (detailed code implementation can be found in Appendix C):

*"You are aged **45-54** with a **high level** of education and you own a **apartment** built approximately **20** years ago with **85** square meters of usable area You live with a **household of 3 people** and the composition is '**2 adults and 1 child'** Your annual household income is **€43000** and your reported wealth is **€150000** You consume about **3500 kWh** of electricity per year and also use gas (**1040 m³** per year) You report '**high'** levels of contact with your neighbors."*

Furthermore, the input incorporates uniformly defined external background information that applies to all household agents. This external information includes two categories: technical attributes (such as annual installation costs of rooftop solar PV and average payback period) and contextual variables (including electricity prices, policy frameworks and subsidies, and the citywide PV adoption rate for the corresponding year). For instance:

{
"Adoption context":
"Only around 7% of households in Amsterdam had installed rooftop solar or heat pump systems in 2021. This means adoption was still relatively rare."
"Financial factors":
"Expect to pay roughly €4,000 to €5,000 for 10 solar panels, excluding btw."
"Annual savings could reach €497, and the estimated payback period was 4 to 9 years, depending

on usage."
"Energy prices":
"Electricity price is €0.136 per kWh (for households using 2,500–5,000 kWh/year)."
"Installation access":
"Apartments often require coordination with neighbors or housing associations to adopt solar PV, but it is still possible."
"Policy and legal environment":
"Some incentives are available, like Salderingsregeling (netting scheme)."
"However, state-protected historic buildings (often older homes) require special permits for rooftop installations."
}

All input information including household profile and contextual background will be integrated into a complete prompt and communicated to the LLM via natural language.

5.2.2 Prompt design

While there is no universally accepted standard for prompt design in academic research, this study follows established good practices from LLM developers. According to OpenAI's prompt engineering guidelines [2], effective prompts usually include identity, instructions, examples, and context components arranged in a structured manner. They also suggest a function-argument paradigm with both system messages and user messages. To be specific, system messages provide basic rules and logic, while user messages supply specific inputs and configuration. Similarly, according to Amatriain's framework [3], prompts usually combine instructions, questions, input data, and examples, while only the first two components are mandatory for every application. It should be noted that while available guidelines provide a methodological framework, the specific implementation represents a researcher's decision tailored to this particular research context and objectives.

Following the recommendations, we adopt a structure that combines identity, input data and instructions in prompt design for PVAgent. First, we establish the model's identity as an Amsterdam resident and set the background year to 2021. This ensures historical consistency in responses. Second, we provide clear instructions for the decision-making task. Specifically, the model is asked to make a judgment on "whether to adopt solar energy." Third, we supply relevant input data for reasoning. This includes household profiles and external background information (see section 5.2.1). Finally, we instruct the model to output only in JSON format to ensure structured material for further analysis. While examples are often recommended in prompt design, we deliberately exclude them to avoid biasing the model toward specific decision patterns.

To make the reasoning process more consistent with actual decision-making, we provide natural language instructions in prompts to suggest that the agent should comprehensively consider multiple dimensions. The prompt also emphasizes hesitation, complexity, and irrational behaviors that are common in reality. This approach aims to avoid responses based on the "rational person" assumption. Below is an example of the user prompt:

```
"You are a household living in Amsterdam in the year 2021.\n"
"Based on your household's situation and the policy environment at the time, think carefully about whether you have already installed rooftop solar panels—or whether you are genuinely and actively considering doing so.\n"
"Consider your financial capacity, energy usage, social context, and environmental motivation and so on to see if there are strong reasons.\n"
"Also consider the complexities and frictions involved, such as your household size and energy demanding, social context, and the potential difficulties in coordinating installation.\n"
"Even if solar panels seem financially beneficial in theory, many households delay or reject adoption due to hesitation, uncertainties, or competing priorities.\n"
"Many families also have concerns about the process being complicated, time-consuming, or uncertain. While some may have strong environmental motivation or financial incentives, the real-world barriers to adoption can often outweigh these motivations.\n\n"
f"Here is the contextual information as of 2021:\n{EXTERNAL_INFO_2021}\n\n"
f"Here is your household profile:\n{profile}\n\n"
"Do not assume a yes or no decision based solely on your dwelling type."
"Please respond in the following JSON format:\n"
"{\n"
'    "decision": "yes" or "no",\n'
'    "reasoning": "A detailed explanation about your decision (2-3 sentences)..."\n'
"}"
```

This study also sets up a system message for the LLM in addition to the user prompt. The following points are emphasized in this message to further standardize the LLM's function and decision logic:

1) Reminding the model to balance economic and non-economic motivations when making decisions;
2) Avoiding the direct inference of behavioral outcomes based only on housing type; and
3) Stressing the importance of behavioral barriers and psychological friction in energy adoption decisions.

By implementing these measures, we can enhance PVAgent's stability and realistic fit to some certain extent. This was necessary because early tests revealed that the LLM tended to automatically reject the possibility of adoption for all apartment residents based solely on housing type, and to make decisions simply based on financial factors.

5.2.3 Model Application and Output

In this study, we implement the agents with OpenAI's GPT-4o-mini (gpt-4o-mini-2024-07-18). The temperature parameter is set to 0 to ensure consistent outputs while reducing random fluctuations. Additionally, we enforce JSON as the response format to enable direct parsing of returned content into dictionary format.

For each household's input data, the model returns a JSON structure containing two key fields: One is "Decision", a binary outcome ("yes" or "no") indicating the adoption choice. The other is "Reasons", including a concise explanation of the decision rationale in 2-3 sentences.

Below is an example of the output:

Decision: “yes”
Reasons: “Given our high income and wealth, we have the financial capacity to invest in solar panels despite the initial costs. Our strong connection with neighbors and the relatively modern age of our apartment make coordination for installation feasible. Additionally, our environmental motivation aligns with the growing trend towards sustainability, and the potential savings on energy bills further incentivize us to proceed with the installation.”

Decision: “no”
Reasons: “Despite having a decent income and a moderate energy consumption, the complexities of coordinating with neighbors in my apartment building and the uncertainty surrounding the installation process make me hesitant. Additionally, my low level of contact with neighbors means I lack the social support that could facilitate this decision, and the upfront costs, even with potential savings, feel daunting given my current priorities.”

5.2.4 Validation

Based on the design described above, we conduct simulations on the existing household-level dataset in this phase. We generate simulation results for 574 household samples. To investigate the effectiveness and rationality of PVAgent in simulating solar energy adoption choices, we perform validation with the following two steps:

First, we validate the model outputs through human evaluation to ensure structural compliance and logical consistency. Two external researchers with expertise in energy transition and urban data studies conduct independent assessments to enhance objectivity. The evaluation framework examines three key aspects: structural adherence to predetermined formats, consistency between reasoning and input information, and the presence of behavioral heterogeneity with realistic logic. Results indicate that in most samples, the model is able to make reasonably differentiated inferences based on individual characteristics and contextual environments. It also explains adoption or rejection motivations in relatively authentic human tones, demonstrating strong language comprehension and decision expression capabilities. However, while the current validation approach provides initial evidence of the model's effectiveness, we acknowledge that direct interviews with actual adopters and non-adopters would provide stronger validation, which is a significant recommendation for future research.

Second, we conduct a preliminary validation of the model's rationality by examining overall adoption trends. We compare the simulated adoption results with the actual adoption status recorded in the WoON dataset [1]. It is important to note that although this field exists in the original dataset, it is not used as a supervisory signal during the model's reasoning process, thus serving as a relatively independent external reference benchmark.

We first compare the overall adoption rate generated by the simulation with the actual adoption rate in the real data. Results show close alignment at the aggregate level. This indicates that the model, without relying on real labels, is already capable of capturing macroscopic decision tendencies to a certain extent.

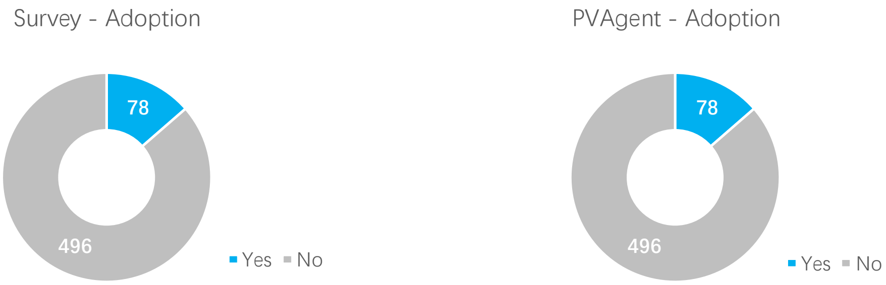

Figure 5-3 Comparison of adoption rate: real-world survey data vs. simulation results

Building on this, we conduct further aggregated analyses around several key variables. We compare the model output results with group trends in actual adoption data. The analysis reveals that the model effectively reproduces the directional patterns observed in reality across most feature dimensions. For example, high-income households and non-apartment housing types show significantly higher adoption rates than other groups. However, we also notice that the model exaggerates positive effects of higher education and higher income as well as negative effects of apartment type of housing. Nevertheless, the model's adoption rate distributions align with actual data trends across multiple important variable dimensions, demonstrating its preliminary capability to extrapolate realistic adoption patterns at the group level.

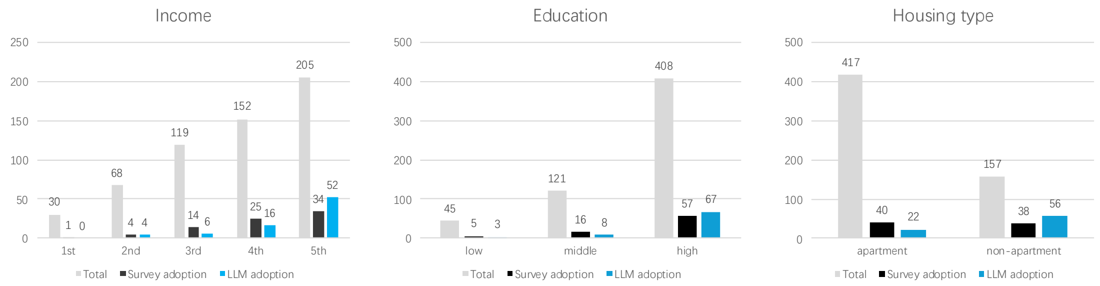

Figure 5-4 Comparison of adoption rate across variables: real-world survey data vs. simulation results

Overall, the validation in this phase demonstrates that the PVAgent, under unsupervised conditions, can generate logically coherent and trend-wise explainable household adoption decision simulation results. Based on this, the next section will further introduce temporal dynamics and neighborhood network to construct a multi-agent simulation framework.

5.3 Phase 2: Dynamic Agent-Based Simulation

In the first phase, we tested the feasibility of using PVAgent to generate household adoption decisions in a static environment. However, real-world solar PV adoption depends on more than individual characteristics and single-year conditions. It also shows patterns over time and is influenced by neighborhood effects [4], [5]. To better capture how households make decisions within social networks, we further incorporate a multi-agent system with temporal dynamics in the model during the second phase.

In this phase, we introduce a neighborhood network where multiple household agents interact and influence each other. Each simulation round represents one year. During each round, agents consider their own characteristics and the surrounding environment while also consulting their neighbors' previous adoption patterns to update their views and decisions. This approach allows us to better understand how solar technology spreads across social networks and track the effects of incentives and social norms by time.

5.3.1 Neighborhood Network Construction

To model the impact of neighborhood impacts, we create a "neighborhood network" that represents social interactions among households. Each household agent is allocated a certain number of neighbors or peers who represent information sources that might impact their energy decisions. According to McPherson's homophily theory [6], people tend to establish and maintain social connections with similar individuals. This phenomenon shapes social network structures and influences information flow and social interaction patterns. On the other hand, Rogers mentioned in the Diffusion of Innovations Theory [7] that non-structural contacts are equally important. This means that the diffusion process relies not only on imitation within close groups but also on information breakthroughs brought by “outsiders” or heterogeneous contacts. Therefore, we design a hybrid neighborhood structure that considers both stable structural connections and a certain proportion of dynamic random contacts, see Figure 5-5.

To be specific, fixed neighbors are chosen based on similar socioeconomic traits like income,

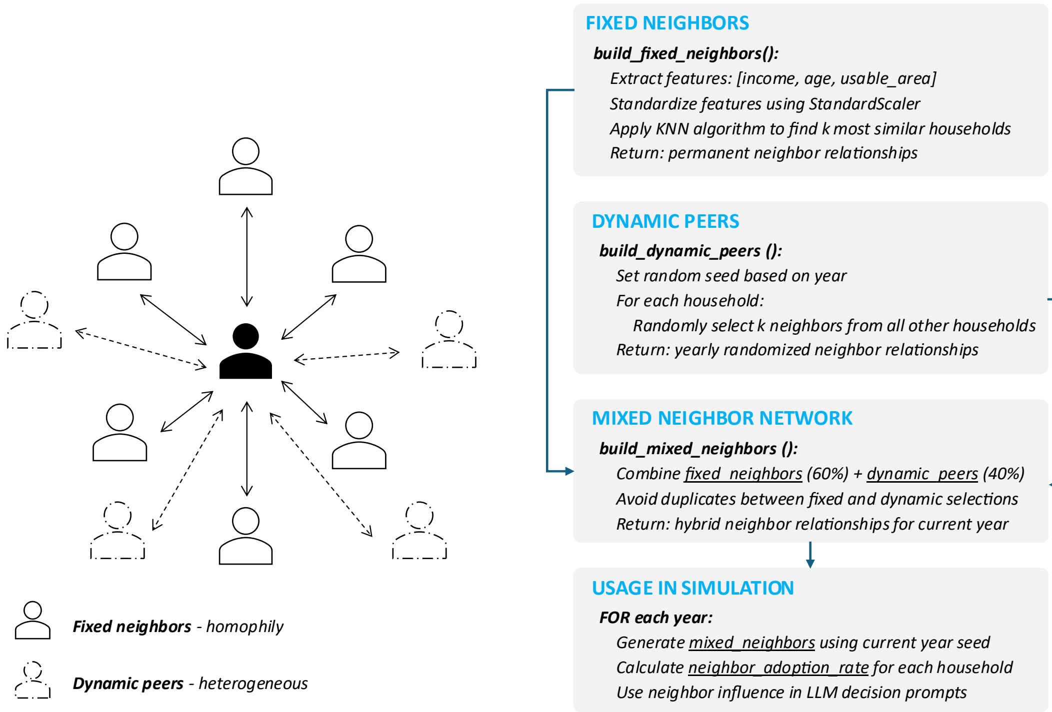

Figure 5-5 Pseudocode of neighborhood network (the detailed code is available in Appendix C)

age, and education. We use the K-nearest neighbors (KNN) algorithm to find the most similar households for each agent. This approach simulates the social relationships produced by “homophily” in real life. Dynamic peers are randomly assigned to each agent in each simulation year, reflecting short-term interaction possibilities such as changes in social circles and temporary information sources. Random seeds are set to ensure reproducibility of results.

We combine both neighbor types for each agent, with 40% being dynamic neighbors and the rest being fixed neighbors in this study. We then calculate how many of these neighbors have adopted solar panels. To avoid issues like randomness with small sample sizes, we convert these adoption rates into descriptive natural language phrases like "very few," "a couple of," "some," or "a significant portion of your neighbors" (see table 5-2). During the simulation, agents who report stronger neighborhood connections are more likely to adjust their views and decisions based on what their neighbors have done in previous years.

Table 5-2 Neighborhood adoption rate and corresponding description

Neighbor adoption rate	description
0	None of your close neighbors have installed solar panels yet.
<= 0.1	Very few of your close neighbors have installed solar panels yet.
<= 0.2	A couple of your close neighbors have installed solar panels yet.
<= 0.3	Some of your close neighbors have installed solar panels yet.
<= 0.5	A significant portion of your close neighbors have installed solar panels yet.
<= 0.7	Many of your close neighbors have installed solar panels yet.
> 0.7	Most of your close neighbors have installed solar panels yet.

Additionally, the model also includes the previous year's overall neighborhood adoption rate as background information. This means agents are influenced by both their immediate neighbors and the broader community trends. This approach gives agents the opportunity to learn about adoption patterns from different social groups in their neighborhood while maintaining their social characteristics and primarily interact with similar households.

5.3.2 Temporal Dynamic Modeling

To simulate the year-by-year development of solar energy adoption behavior within neighborhoods, we create a multi-year simulation framework running from 2021 to 2024. Every year, the model updates agent status, assesses neighborhood influence, and applies the LLM to make adoption decisions.

The annual evolution process includes the following key updates:

1. **Individual Attribute:** Each year, individual characteristics are updated, such as income growth and changes in energy use, to reflect yearly demographic and economic dynamics.
2. **External Environment:** This component incorporates key yearly context variables, including political developments, electricity prices, market conditions, and other context-specific factors that reflect the broader reasoning background.
3. **Neighborhood Network:** While fixed neighbors remain the same, dynamic peers are refreshed to represent changing social connections. Additionally, we also include the

previous year's community-wide adoption rate to provide broader context.

4. **Memory of Past Decisions:** Once a household answer “yes” and adopts solar panels, it keeps this status in following years.

The detail code is available in Appendix C. This approach allows us to track how individual decisions evolve over time as they respond to social influence and external changes.

5.3.3 Prompt Design

This stage continues the basic structure of "context + profile + JSON format output" from Section 5.2 in prompt design (see 5.2.2 for details). However, to simulate the dynamic evolution process, two key extensions were made to the prompt content:

Time Awareness: In each simulation round, agents are set to "live in a specific year (such as 2023)," and their decisions must be based on the policy background and social context of that year. This information is clearly given in the prompt, allowing the model to make decisions with temporal consistency.

Neighborhood Influence: During each year's simulation, each agent is notified about their neighborhood adoption rate. This information is embedded in the profile section of the prompt, enabling the LLM to respond to the peer effect from the agent’s social network.

5.3.4 Validation

Based on the above design, we conducted multiple rounds of behavior simulation using the LLM-based agent model with time evolution and neighborhood networks in this phase. Taking Oude Pijp (n=2165) as an example, we generated four-year (2021-2024) sequence of household adoption decision dynamics. To verify effectiveness and reasonability, we evaluated it through the following two steps:

We began by manually reviewing the yearly decision results generated by the simulation, focusing on whether individual behaviors remain consistent over time and whether they reflect social influence and personal differences. A set of household decision paths was randomly selected, each including yearly decisions and the associated reasoning. Two external researchers with expertise in urban energy transition and urban data science from TU Delft were invited to conduct independent evaluations. The assessment criteria included rational behavioral progression, impact of neighborhood adoption, and reflection of common real-world patterns like "hesitation - influence - change" or prolonged indecision. The results demonstrated that in the majority of cases, the model offered logical and credible decision-making processes. Some households demonstrated evident adjustments as a result of surrounding adoption patterns or changes in energy costs, but others remained non-adopters due to financial restrictions or a lack of motivation. Overall, the PVAgent captured a believable track of behavioral change over time. Figure 5-5 shows two examples of the outputs.

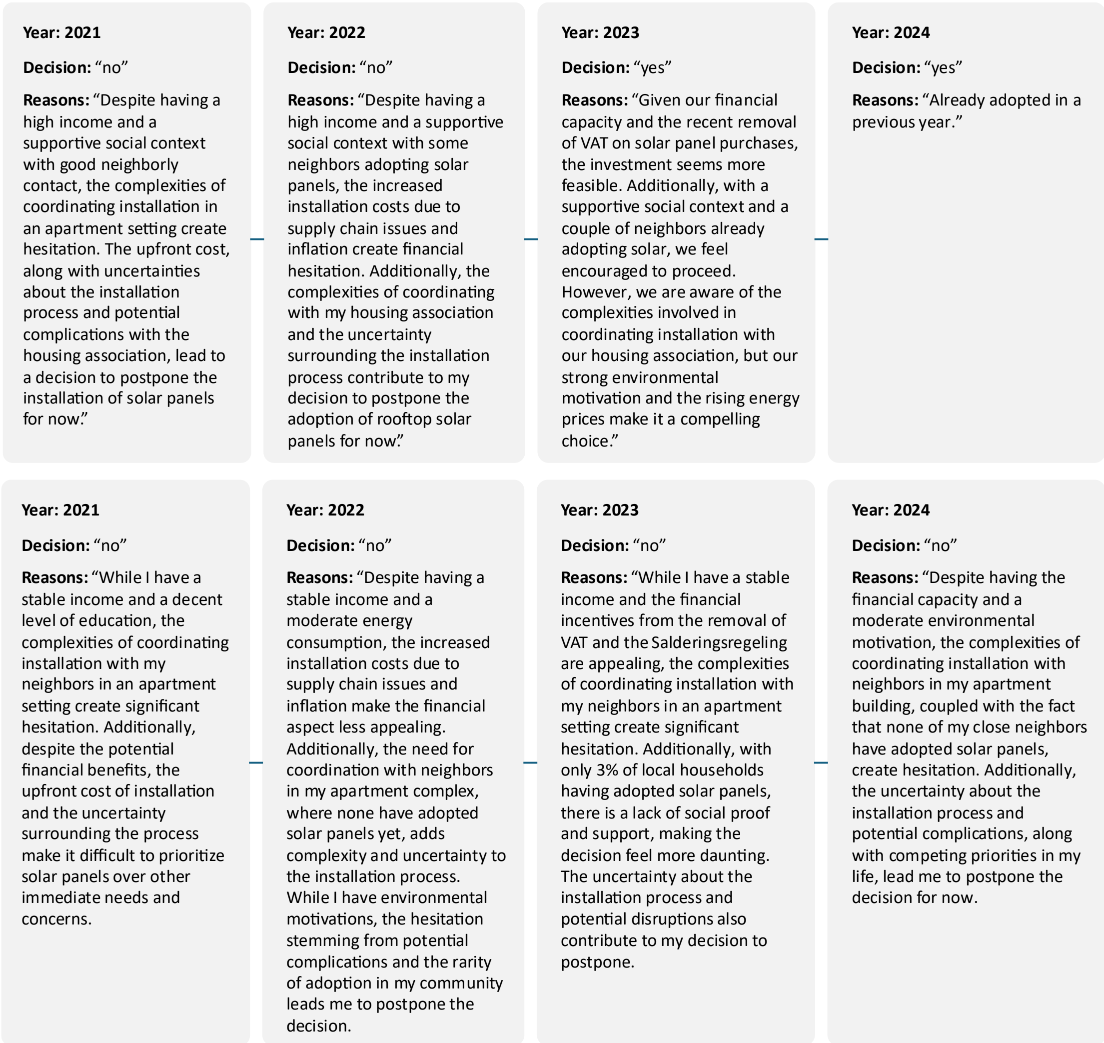

Figure 5-5 Examples of household decision trajectories: "hesitation → influence → change" and prolonged indecision patterns

Second, we tested whether the model could capture group-level behavioral patterns by comparing the simulated adoption rates in Oude Pijp to real-world solar adoption data from BBGA [8]. Even without actual data as a training input, the model's yearly adoption rates closely matched actual patterns, as seen in Table 5-3. We also examined how key variables were related to adoption decisions and found that the model effectively reproduced the nonlinear impact of social influence. Differences in adoption rates across income levels and housing types reflected the same structural patterns observed in real data.

Table 5-3 Comparison of adoption rates: real-world data vs. simulation results

Year	Real-world data	Simulation result
2023	4%	4%
2021	4%	3%

In conclusion, while the PVAgent may still simplify individual-level behavior to some extent, the second-stage simulation captures reasonable decisions change at the individual level and meaningful dynamics at the aggregate level across multiple dimensions, demonstrating its potential for analyzing household energy decisions.

5.4 Summary

This chapter focuses on the development of PVAgent, the LLM-based household agent. It includes a detailed introduction of the model's design modules per phase and the assessment of its effectiveness in modeling household solar adoption decisions. This addresses the study's second research question.

The model development proceeds in two phases. The first phase uses a static population sample and individual agent system, focusing on how individual characteristics and external factors influence decision-making. Relevant factors are converted into natural language inputs that the LLM-based agent could comprehend. The second stage builds on this foundation by incorporating neighborhood networks and temporal dynamics, allowing for cross-year multi-agent modeling.

Model validation is carried out using both manual logic examination and comparisons to real-world data patterns. The results show that the agent can develop appropriate decision logic and reasoning at the individual level, as well as reflecting group-level structural differences and diffusion patterns seen in reality. These findings indicate that the model has preliminary explanatory power and generalization potential.

However, there are some limitations. The agent's reasoning is entirely dependent on the information presented in prompts, with no systematic memory mechanism or long-term preference modeling. Neighborhood structures are now a combination of static design and random disturbance, which does not fully capture the diversity of real-world social networks. Furthermore, the absence of a reliable feedback mechanism limits the model's ability to learn from real-world outcomes and iteratively improves its predictions through closed-loop validation.

Beyond these technical limitations, the model development and validation are exclusively focused on Amsterdam as a case study. Therefore, we encourage future research to explore how different contexts shape model outputs by testing the framework in diverse settings. This would provide further insights into the model's generalizability.

In conclusion, this chapter demonstrates the LLM-based agent’s capability to simulate decisions at both individual and aggregate levels with reasonable coherence. The following chapter will examine the insights gained from the simulation results in greater detail. Furthermore, the model's applicability bounds and potential areas for future development will be discussed in Chapter 7.

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Chapter 6 Insights from LLM-based Agent Model Simulations

In the previous chapter, we developed and validated the capability of LLM-based agent model (PVAgent) in simulating household solar energy adoption decisions. This chapter focuses on the simulation results to analyze how solar PV adoption behaviors evolve dynamically across different neighborhoods. We aim to understand the motives and barriers that influence adoption decisions, explore behavioral differences across various social groups and temporal dimensions, and provide targeted insights for future policy making. Due to space constraints, we select three neighborhoods with significant socioeconomic differences, which are Oude Pijp, Slotervaart-Noord, and Omval/Overamstel. These neighborhoods serve as case studies to demonstrate our simulation and analytical results. Their locations, socioeconomic characteristics, and sample sizes are shown in Figure 6-1 and Table 6-1.

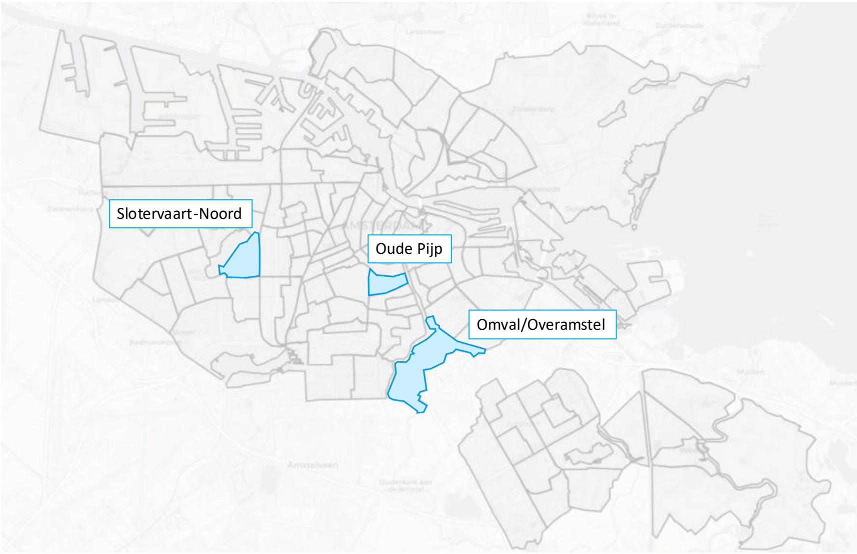

Figure 6-1 Location of three selected neighborhoods

Table 6-1 Socioeconomic characteristics of selected neighborhood (data source: BBGA [1])

Neighborhood	Mean disposable household income	Owner-occupied housing (%)	Single-family housing (%)	Average number of residents per household	number of households (n=)	number of owner-occupied households (n=)
Oude Pijp	48300	22.8	0.6	1.54	9494	2165
Slotervaart-Noord	42200	31.8	29	2.35	3736	1188
Omval/Overamstel	60500	14.3	0.8	1.3	3400	486

The main simulation outputs, including the overall adoption rate and temporal diffusion process are shown in section 6.1. Section 6.2 analyzes the motivations and obstacles that affect adoption decisions. Section 6.3 examines the policy and implementation implications of these results. Building on this framework, this chapter contributes to addressing the third research question of this study: How can simulation results from LLM-based agents inform policy recommendations for solar PV adoption?

6.1 Simulation results of adoption decision

This section shows the simulation outcomes generated from the PVAgent model and the disparities in solar PV adoption among various neighborhoods and socioeconomic groups. The simulation covers the period from 2021 to 2024, spanning four time steps.

6.1.1 General Trends

Figure 6-2 shows the changes in PV system adoption rates across three representative neighborhoods in different years:

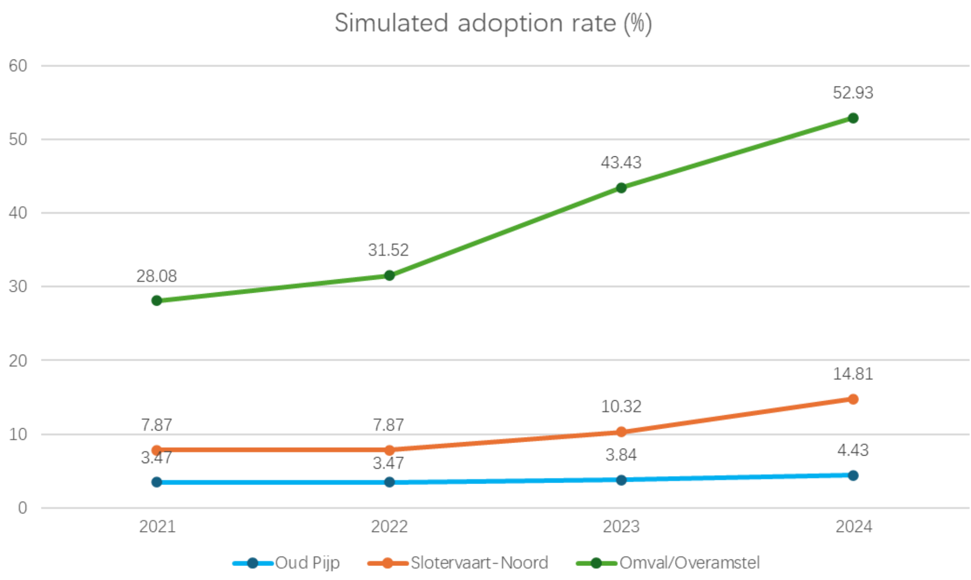

Figure 6-2 Simulated adoption rate in three neighborhoods from 2021 to 2024

From a spatial perspective, Oude Pijp consistently shows PV adoption rates below the Amsterdam average (7% in 2021 and 9% in 2023), reflecting potential structural resistance including housing type constraints and neighborhood attitudes. Slotervaart-Noord demonstrates steady growth patterns, with adoption rates roughly aligned with the city average. In contrast, the adoption rate in Omval/Overamstel is significantly higher than the average, even exceeding 25% in 2021, indicating substantial diffusion potential and favorable adoption conditions.

Table 6-2 further shows the annual growth rates (%) for the three neighborhoods during 2022–2024. Overall, residential solar PV diffusion accelerates year by year. In 2022, growth in all three neighborhoods is rather mild, which may be attributed to global supply chain tensions that led to cost increases. Since 2023, the adoption rate has increased dramatically, possibly due to the combined effects of declining costs, policy incentives and peer influences. Notably, Omval/Overamstel's growth rate appears to be decreasing in 2024, which aligns with the S-curve pattern where technology diffusion slows as adoption rates reach higher levels [2], [3].

Table 6-2 Simulated growth rates for each neighborhood (%)

Neighborhood	2021 -> 2022	2022 -> 2023	2023 -> 2024
Oude Pijp	0	10.66	15.36
Slotervaart-Noord	0	31.13	43.51
Omval/Overamstel	12.25	37.79	21.87

6.1.2 Household Characteristics and Adoption Behavior

This section further examines how different household characteristics influence solar PV adoption patterns in our simulation. Generally speaking, households living in non-apartment dwellings with higher income, higher education levels, larger livable areas and household sizes, and higher power consumption demands are more likely to adopt solar PV. This conclusion is consistent with the previous research findings identified in our literature review (Chapter 4). However, the model also reveals certain noteworthy outliers and non-linear patterns.

First, regarding income, the simulation results show a strong positive relationship between solar PV adoption and income level. The highest income group demonstrates adoption rates substantially higher than other groups throughout the simulation period. In 2024, this group reached 25.43% adoption, significantly higher than the fourth quintile's 8.57%. This indicates that financial capacity remains the primary condition affecting residential solar PV adoption.

However, despite having less financial capability, the second quintile consistently shows slightly higher adoption rates than the third quintile. For example, in Omval/Overamstel, the 2nd quintile adoption rate in 2024 was 4.55%, higher than the 3rd quintile's 3.17%. This trend might be due to the influence of other non-economic factors, such as neighborhood effects, housing type differences, or household energy consumption patterns.

Table 6-3 Simulated adoption rate per income quintile* (%)

Income quintile	2021	2022	2023	2024
1st	0	0	0	0
2nd	2.66	2.66	3.87	5.33
3rd	0.88	1	1.63	3.13
4th	4.76	4.76	6.55	8.57
5th	15.32	16.3	20.65	25.43

* the definition of income quintile is based on BBGA's [1] category. (1st quintile: 0-23.475, 2nd quintile: 23.476 - 34.144, 3rd quintile: 34.144 - 48.551; 4th quintile: 48.551 - 68.311, 5th quintile: 68.311 and more)

Second, there is generally a positive relationship between education level and adoption rates (Table 6-4). The highly educated group achieved an average adoption rate of 16.16% in 2024, significantly higher than those with medium education (8.25%) and low education (4.51%). However, in Omval/Overamstel, a high-adoption area, the medium education group's adoption rate (45%) is higher than that of the highly educated group (25.38%), as shown in Table 6-5. This phenomenon suggests that the relationship between education level and adoption behavior varies across regions and may be influenced by local environmental factors and other neighborhood characteristics.

Table 6-4 Simulated adoption rate per education level group (%)

Education level	2021	2022	2023	2024
high	9.03	9.63	12.7	16.16
middle	6.09	6.09	6.98	8.25
low	1.64	1.64	2.46	4.51

Table 6-5 Simulated adoption rate in 2021 per education level in each neighborhood (%)

Education level	Oude Pijp	Slotervaart-Noord	Omval/Overamstel
high	4.37	10.68	25.38
middle	0.92	2.93	45
low	0	0	16

Furthermore, dwelling type significantly influences PV adoption behavior, as shown in Table 6-6. In 2024, households living in dwellings other than apartments achieve an adoption rate of 30.48%, which is much higher than 8.83% for apartment residences. This aligns with expected limitations regarding installation physical conditions, rooftop ownership, and collective decision making [4], [5]. However, in terms of diffusion speed, households living in apartments have shown higher adoption growth rates than non-apartment residents (Table 6-7). This trend may indicate that, on one hand, non-apartment residential adoption is gradually approaching saturation. On the other hand, adoption barriers in apartment buildings are being progressively overcome through policy guidance, neighborhood collaboration, and collective action interventions such as shared rooftops, with consensus among neighbors gradually emerging.

Table 6-6 Simulated adoption rate per dwelling type (%)

Dwelling type	2021	2022	2023	2024
Apartment	3.59	4	6.35	8.83
Non apartment	22.61	23.17	26.1	30.48

Table 6-7 Simulated growth rates for each dwelling type (%)

Dwelling type	2021 -> 2022	2022 -> 2023	2023 -> 2024
Apartment	11.42	58.75	39.06
Non apartment	2.48	12.65	16.78

Additionally, research on age variables has not yet reached the conclusion in existing literature [6], [7]. Our simulation results support the view that the mid-age groups (especially 35–44 and 55–64) are more inclined to adopt rooftop PV systems (Table 6-8). Across the

Table 6-8 Simulated adoption rate per age group (%)

Age	2021	2022	2023	2024
17-24	0	0	0	9.09
25-34	2.73	3.25	5.46	6.63
35-44	13.5	13.74	16.97	21.62
45-54	6.87	7.11	8.67	11.33
55-64	10.46	10.78	13.63	16.16
65-74	9	9.8	12.6	16
75 and older	2.08	3.11	5.54	8.65

three neighborhoods, adopters in Omval/Overamstel are generally older than those in the other two, potentially related to higher overall wealth, larger household size, and relatively stable residence duration.

Table 6-9 Simulated adoption rate in 2021 per age group in each neighborhood (%)

Age	Oude Pijp	Slotervaart-Noord	Omval/Overamstel
17-24	0	0	
25-34	0.62	2.78	12.04
35-44	6.08	19.92	30.7
45-54	3.52	7.66	19.8
55-64	4.73	3.29	53.75
65-74	4.3	6.06	41.07
75 and older	0	1.02	13.89

In summary, individual and household characteristics have significant influence on residential solar PV adoption decisions. Complex interactions exist among variables such as income, education, and dwelling type, with their effects varying according to regional contexts, policy backgrounds, or neighborhood characteristics. In most respects, the simulation results are consistent with previous study findings (e.g., [8]). More across group analysis broken down by year and zone can be found in the Appendix D.

Importantly, the simulation reveals non-linear patterns, indicating that factors influencing PV adoption do not operate independently or exhibit simple linear relationships. Instead, they result from interactions among multiple social, economic, and spatial mechanisms. Therefore, the next section will further analyze the motives and barriers exhibited by these simulated households during their decision-making processes, to gain deeper understanding of the underlying behavioral mechanisms.

6.2 Motives and Barriers

As described in Chapter 5, PVAgent not only records whether households adopt solar PV systems but also generates their decision-making reasoning processes. Based on these reasoning outputs, this section systematically extracts the motives and barriers manifested by agents in their adoption decisions, categorizes and analyzes them according to the factor classification framework proposed in Chapter 4.

6.2.1 General Patterns Across All Households

To understand the motivations and barriers associated with solar PV adoption at the aggregate level, we first analyzed the reasoning outputs of all households (n=3898) across neighborhoods in the initial simulation year (2021). Figure 6-3 and 6-4 presents frequency statistics of different types of motives and barriers mentioned in the reasoning texts. It should be noted that agents often cite multiple factors simultaneously in their reasoning, which means these motives are not mutually exclusive.

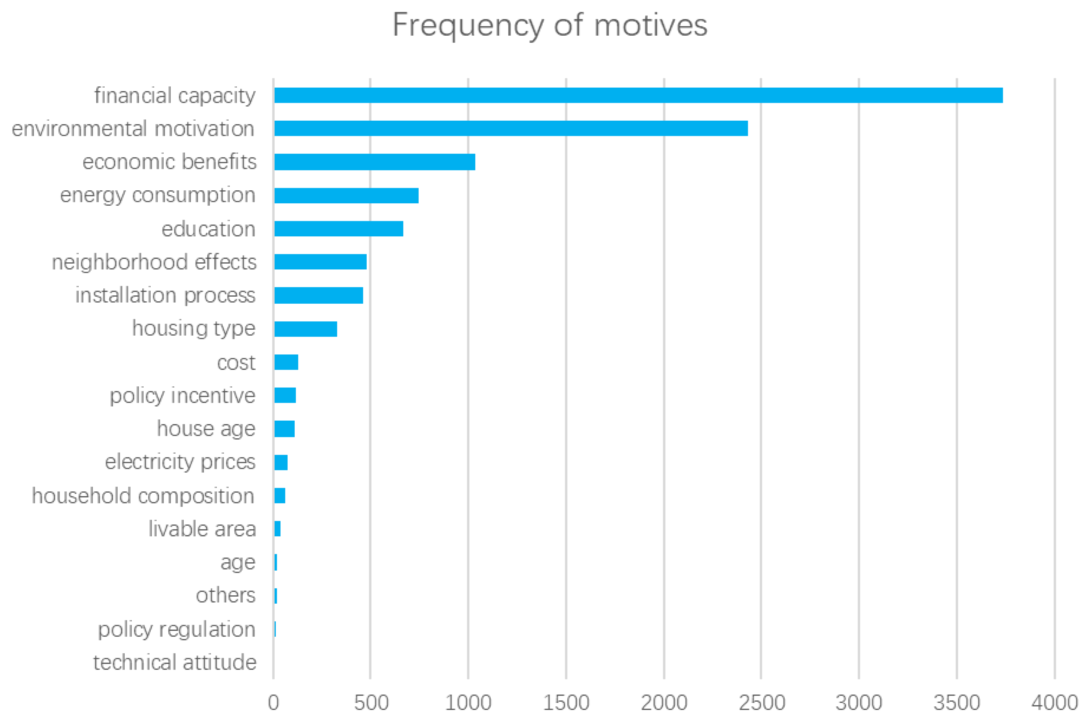

Figure 6-3 Frequency of motives mentioned in reasoning across all households

Among all motives, financial capacity is mentioned most frequently, indicating that under scenarios with high initial investment costs, having sufficient economic resources is a key prerequisite for household decisions on technology adoption. Economic benefits are ranked third as a high-frequency consideration, which are related to possible energy bill savings and an acceptable payback period. At the same time, energy consumption is also a high-frequency motivator, indicating that high-consumption households are more inclined to explore alternative energy options to reduce energy costs.

Environmental awareness is also widely mentioned in the argument, although its influence appears secondary compared to financial factors. This suggests that while environmental motivation may not be the primary driver, it does have a significant influence on certain households. Education level, being the fifth most common component, demonstrates its indirect influence on adoption behavior. Highly educated households tend to have superior knowledge acquisition and technological acceptance capacities, as well as higher environmental consciousness, making them more psychologically and cognitively open to residential solar PV installation [9].

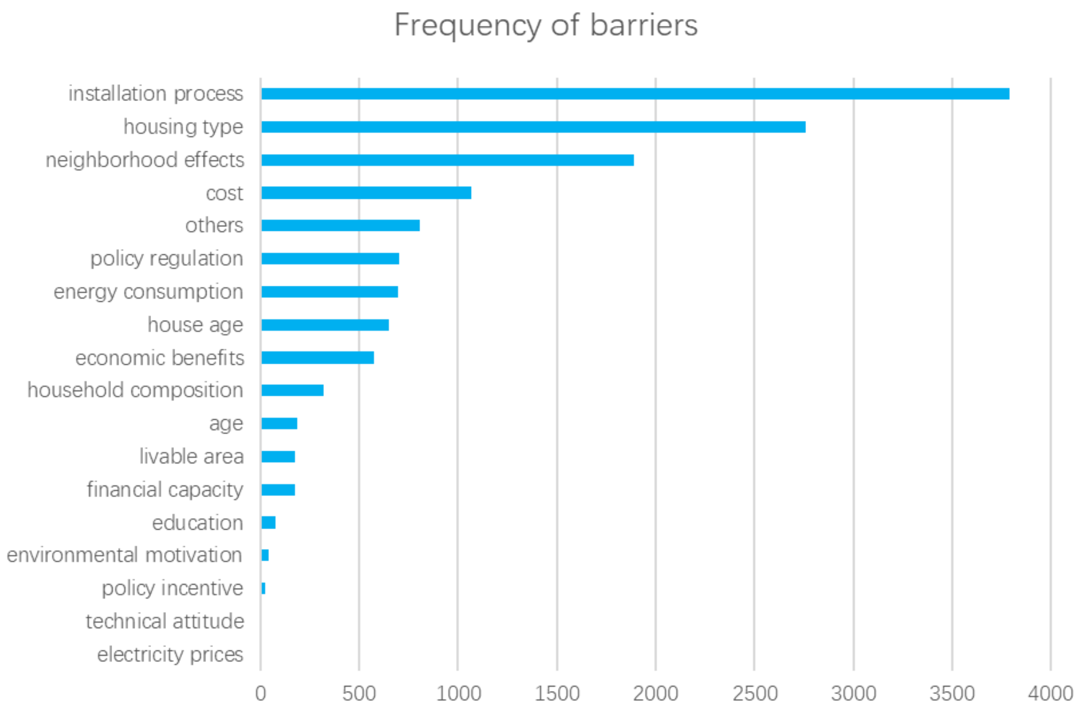

Figure 6-4 Frequency of barriers mentioned in reasoning across all households

As shown in Figure 6-4, the most frequently reported barrier is the concerns around the installation process. This includes the complexity and uncertainty of the installation process, and difficulty in coordinating with other stakeholders such as neighbors, housing organizations, and suppliers. Dwelling type ranks second, particularly multi-story apartments, whose structural limitations and installation complexity constitute important factors constraining system adoption. Neighborhood effects are also frequently mentioned in the reasoning. It suggests that households in areas with lower PV adoption rates often face higher uncertainty and tend to adopt a wait-and-see attitude. This finding aligns with [10] who found that Dutch households strongly rely on their surroundings when making decisions to reduce uncertainty.

The cost burden as a barrier factor contrasts with financial capacity and economic benefits as motivators. When initial investment costs are high and expected returns are unclear, many households will postpone or deny adoption decisions. Related to this, the energy consumption level is also frequently mentioned. For households with low electricity usage, installing PV systems is considered to have an unfavorable payback period.

Finally, policy regulations and building age are another significant set of barrier factors. Many households living in historical buildings may face dual challenges: structural unsuitability for PV installations and stricter policy approval requirements in heritage protection areas. The combination of policy and physical conditions undermines the feasibility of PV systems in such dwelling types.

6.2.2 Comparative Analysis Between Adopters and Non-adopters

To further understand decision-making differences, we combine households' final decision outcomes with their reasoning processes to compare how adopters and non-adopters mention motivational and barrier factors. Overall, the findings are consistent with general patterns: financial capacity and expected economic benefits remain the core motivations for adopters, while non-adopters primarily cite installation process complexity, dwelling type limitations, and upfront costs as their main deterrents (see Figure 6-5 and 6-6).

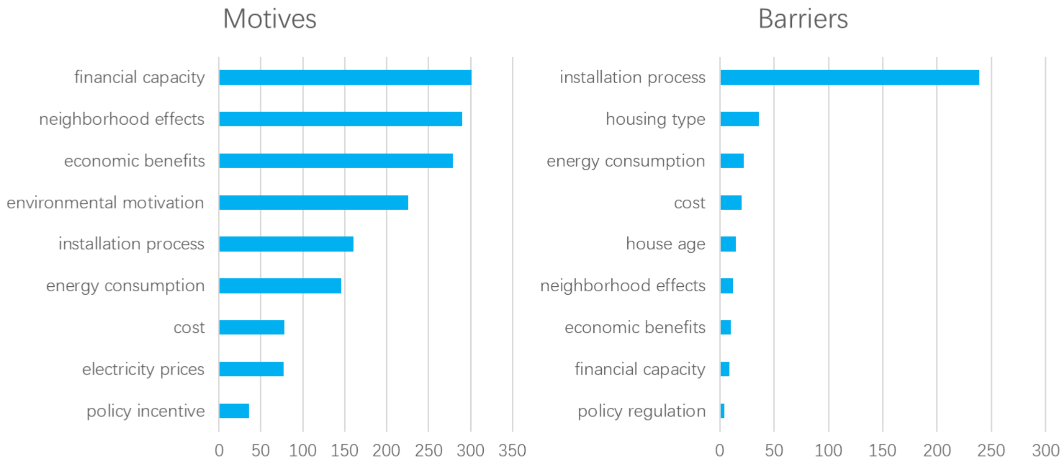

Figure 6-5 Motives and barriers mentioned by household making "yes" decision

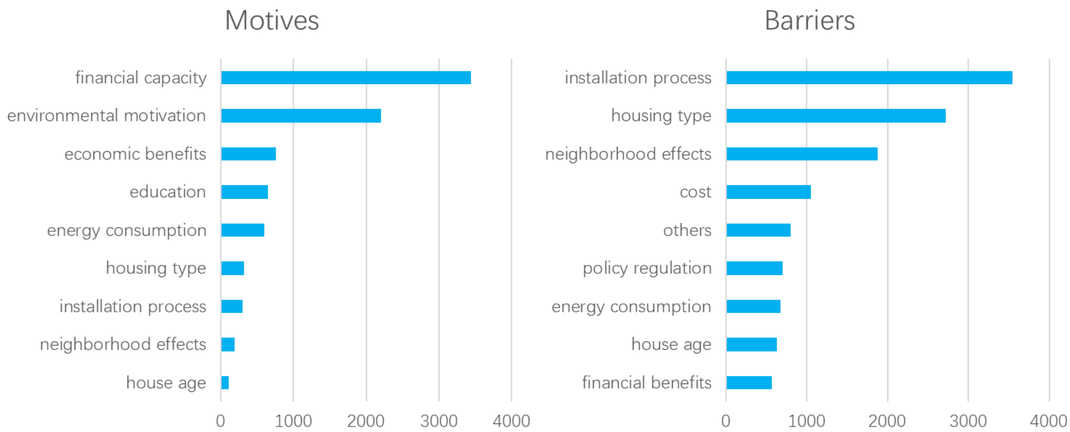

Figure 6-6 Motives and barriers mentioned by household making "no" decision

A noteworthy phenomenon is that the installation process exhibits influence in dual directions. Among the adopter group, it is both frequently mentioned as a concern and as a facilitating factor. Specifically, some adopters believe that clear guidance, controllable scheduling, and effective coordination mechanisms during installation actually enhance their confidence and promote adoption. However, a considerable portion of adopters also express concerns about the uncertainty and complexity during installation, showing that communication coordination and technical implementation uncertainties still have significant influence in the decision-making process. This supports [10], who highlighted how transactions with external parties create additional indirect cost barriers.

Additionally, neighborhood influence affects adopters and non-adopters differently. The primary reason may be that adopters are more likely to have peers who adopted solar systems [11]. Neighborhood effects are stated as positive motivation among adopters, with their frequency even exceeding that of environmental awareness. This demonstrates that visible adoption, experience sharing, and peer influence create positive spillover effects that motivate collective action [12]. Conversely, in non-adopters' reasoning, neighborhood effects appear more often as barriers. This might be due to a lack of PV installation precedents in the local region, or a conservative attitude toward adoption of new technology, which amplifies individual doubt and reinforces wait-and-see behavior.

6.2.3 Comparative Analysis Across Different Neighborhoods

To further examine how spatial and social structures influence PV adoption behavior, we compare the motivational and barrier factors across the three simulated neighborhoods. Given the different total number of households in each neighborhood, the analysis uses relative frequency of each factor to ensure comparability.

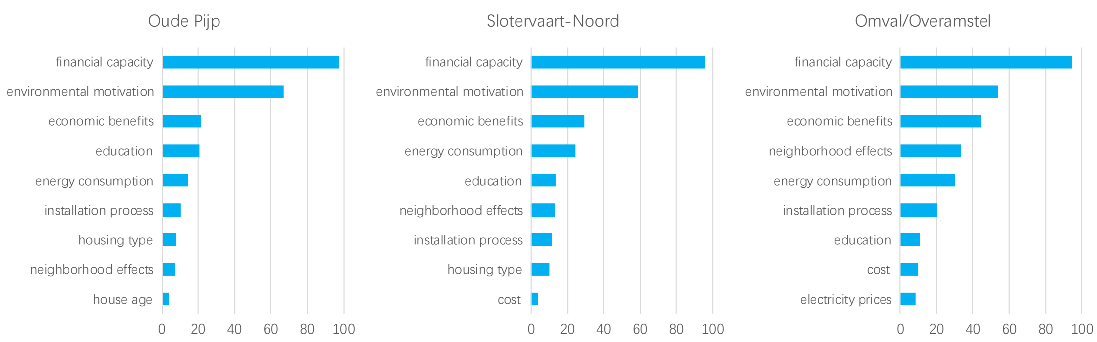

Figure 6-7 Relative frequency of motives in each neighborhood (%)

In terms of motives, the top three most commonly reported motivating variables across all three areas are consistent with overall patterns, but different neighborhoods also exhibit several representative differences (see Figure 6-7). In Overamstel, neighborhood effects demonstrate stronger positive effects, correlating with its significantly higher adoption rate compared to the other two neighborhoods. This suggests that the high density of existing adopters increases demonstration spillover effects in the neighborhood. In Slotervaart-Noord, households consume more energy, making the potential savings from PV systems more appealing, and thus serving as a primary driving factor in this area. The positive impact of education level on adoption behavior is more pronounced in Oude Pijp, likely due to the neighborhood's larger share of highly educated residents. Such households are more likely to have better knowledge acquisition skills and environmental awareness [13].

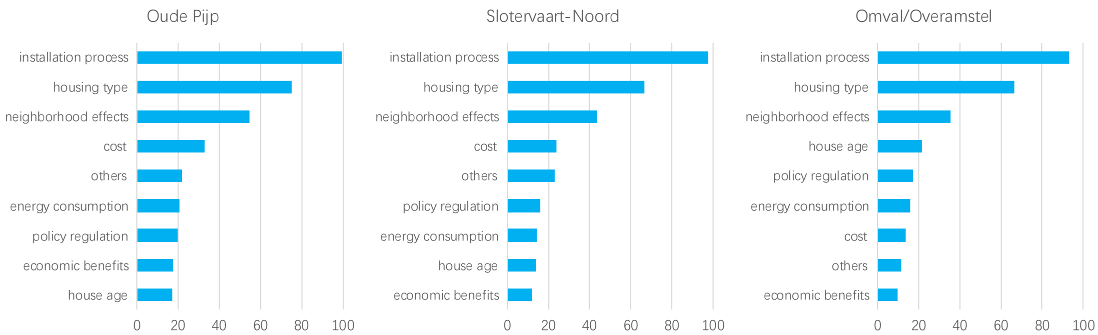

Figure 6-8 Relative frequency of barriers in each neighborhood (%)

Regarding barriers, the three neighborhoods show high consistency in their top-ranked obstacle factors. Installation complexity, dwelling type limitations, and negative effects of low neighborhood adoption rates are all widely mentioned as common structural barriers, as shown in Figure 6-8. However, different neighborhoods show varying degrees of concern for other factors. Households in Oude Pijp and Slotervaart-Noord demonstrate higher sensitivity to cost issues, possibly reflecting that these households face more competing expenditures or have different spending priorities. As a result, even with decent payment capacity, they tend toward more conservative decision-making. In Overamstel, despite its higher overall adoption rate, building age becomes a significant barrier. This reflects the constraints that aging housing stock places on further expanding adoption rates.

In conclusion, household decisions to adopt solar PV or not are impacted by a variety of common variables the same as the overall findings. However, different neighborhoods prioritize different specific factors, demonstrating that adoption behavior is highly contextual and varies by location. This suggests that promotion efforts need to comprehensively consider specific characteristics and neighborhood structures, promoting more targeted support strategies.

6.2.4 Comparative Analysis Across Different Socioeconomic Groups

We further explore the differences in motivations and barriers faced by different socioeconomic groups. Due to space constraints, this section focuses on comparisons between different income groups. The following figures (6-9 and 6-10) show the motivational and barrier factors mentioned by households in different income levels.

	1st	2nd	3rd	4th	5th
age	1.09	0.97	0.88	0.83	0
cost	10.38	3.87	0.75	2.26	4.35
education	24.04	19.85	26.66	19.17	10.17
electricity prices	0	0.24	0.13	0.71	4.23
energy consumption	11.48	9.69	8.26	23.69	25.86
environmental motivation	58.47	60.53	52.82	59.76	70.4
economic benefits	15.3	27.6	24.16	29.17	28.06
financial capacity	83.06	88.86	97.5	98.69	98.77
house age	0	0	1.75	2.02	4.96
household composition	2.19	4.6	1.38	1.19	1.16
housing type	14.75	3.39	5.38	8.93	10.42
installation process	7.1	9.2	7.51	11.55	15.5
livable area	0	0.24	0.25	0.71	1.84
neighborhood effects	3.83	12.83	8.14	8.81	17.22
others	0.55	1.69	0.38	0.24	0.31
policy incentive	1.09	1.21	2.13	2.98	3.98
policy regulation	0	0.24	0	0.48	0.67
technical attitude	0	0	0.25	0.24	0.06

Figure 6-9 Relative frequency of motives per income quintile (%)

As shown in Figure 6-9, financial capability and environmental awareness are the most frequently mentioned motivators across all income levels. However, there are some differences between groups. Highest-income households report these factors at rates of 98.77% and 70.40% respectively, compared to 83.06% and 58.47% among lowest-income households. This trend indicates that advantageous financial conditions enable households to more easily respond to environmental motives and translate them into concrete adoption decisions.

Education is frequently mentioned among households in the first to third quintiles but decreases significantly to 10.17% in the fifth quintile. This pattern indicates that lower- and middle-income households depend more on acquiring knowledge about policies, technologies, and sustainability to drive their adoption decisions, whereas affluent households rely primarily on their financial resources and environmental values.

Additionally, expected economic benefits matter across all income levels but gain prominence among middle-to-high income households, who typically tend to approach PV systems as financial investments. Energy consumption considerations follow a similar upward trend with income, likely because wealthier households consume more electricity and therefore see clearer savings potential [14]. Cost variables, on the other hand, occur more frequently in low-income households' reasoning, reflecting stronger cost sensitivity and wait-and-see attitudes when evaluating the economic benefits of PV systems.

Furthermore, high-income households mention neighborhood influences the most (17.22%). Factors such as electricity prices and policy incentives also have greater positive influence on high-income households than other groups, indicating that these households are more responsive to positive signals in the external environment. Interestingly, high-income groups are also more likely to identify installation process coordination as a motivator, which might be due to their advantages in resource mobilization, time scheduling, and decision-making autonomy [15].

Among barrier factors, concerns regarding installation process are the most often reported barriers across all groups, accounting for nearly 100% of responses. Dwelling type limitations are also significant barriers with relatively small differences between income groups, reflecting that structural constraints such as roof configuration, building conditions, collective decision-making requirements are universally present obstacles. Another common barrier is neighborhood effects, but their influence is relatively lower among high-income groups (37.75% in the fifth quintile vs. 62.3% in the first quintile, see Figure 6-10).

Unsurprisingly, the negative effects of cost and financial capacity decrease rapidly with rising income. Among the lowest income group (first quintile), cost barriers are mentioned at 50.27% and financial capacity limitations at 36.07%, while these figures drop to 17.71% and 1.53% respectively in the fifth quintile. This clearly highlights the critical role of economic resources among low-income households. Moreover, low-income groups are more likely to cite constraints such as small household size, inadequate energy consumption levels, and payback uncertainty as barriers. This indicates that residential solar PV has limited economic appeal when households have lower energy demands. Meanwhile, building age and policy restrictions are becoming more common among high-income groups (21.69% in the fifth quintile), possibly reflecting the fact that these households are more likely to live in historically protected buildings and, despite having renovation intentions and resources, are constrained by policies or installation feasibility.

	1st	2nd	3rd	4th	5th
age	9.29	12.11	7.76	5	0.86
cost	50.27	42.62	35.29	27.38	17.71
education	0.55	6.3	2.5	2.26	0.8
electricity prices	0	0	0	0	0.06
energy consumption	26.78	33.66	31.66	14.17	8.21
environmental motivation	1.09	0.24	1.13	0.6	1.53
economic benefits	24.04	27.85	26.78	11.55	6.37
financial capacity	36.07	10.17	2.88	2.02	1.53
house age	15.3	16.22	18.52	10.36	19.55
household composition	21.86	25.91	12.52	4.76	1.96
housing type	74.86	66.59	71.34	73.33	71.2
installation process	100	98.55	99.75	97.62	96.88
livable area	1.64	2.42	2.63	7.38	4.9
neighborhood effects	62.3	54.96	56.2	57.38	37.75
others	22.4	19.37	17.65	23.57	21.14
policy incentive	0.55	0.48	2.13	0	0.37
policy regulation	10.38	16.95	16.02	15.83	21.69
technical attitude	0	0	0	0	0.06

Figure 6-10 Relative frequency of barriers per income quintile (%)

Overall, high-income households tend to adopt PV systems driven by stronger financial capacity, higher energy demands, and environmental consciousness. They are also more easily influenced by positive external context but still struggle to overcome practical barriers such as dwelling type and building age. This finding aligns with [5]'s conclusions. Low-income groups' adoption decisions rely more heavily on cost considerations while being more constrained by economic burden, lower energy consumption, and insufficient neighborhood support.

6.2.5 Temporal Evolution Trends

In this subsection, we conduct a comparative analysis of motives and barriers mentioned in different simulation years. By observing the relative frequency changes of key factors at different time points, we aim to identify important temporal dynamic characteristics influencing household decision-making, as well as transformation patterns that may be related to policy changes, market environment, or diffusion processes in neighborhood network.

	2021	2022	2023	2024
age	20	5	16	13
cost	131	1586	11	789
economic benefits	1038	775	387	371
education	666	5	9	57
electricity prices	77	358	313	252
energy consumption	748	1275	1645	1736
environmental motivation	2430	84	152	310
financial capacity	3739	3491	3210	2849
house age	112	73	81	62
household composition	63	40	29	33
housing type	329	543	472	321
installation process	461	154	389	278
livable area	39	10	16	8
neighborhood effects	480	282	275	237
others	18	2	2	1
policy incentive	114	2	1380	1290
policy regulation	16	1	27	31
technical attitude	5	0	4	0

Figure 6-11 Frequency of motives mentioned in each year

Figure 6-11 reveals clear structural evolution in adoption motivations over time. Financial capacity remains the most important motivating factor throughout the period, but its relative importance gradually declines year by year. Economic benefits are frequently mentioned in the early period (2021), but gradually lose their dominant position in subsequent years. This pattern reflects that while economic thresholds continue to decrease, the weight of other factors gradually increases. On the other hand, the importance of policy incentives rises significantly, especially with the VAT exemption policy introduced in 2023. This makes it become one of the major driving forces, indicating that institutional support plays an important promoting role in later adoption. Cost reasons are often cited as driving influences in 2022, likely linked to rising solar prices due to global supply chain disruptions and the energy crisis [16], leading some financially equipped families to accelerate their decision-making processes.

Environmental motivation remains high throughout the four years, with a slight recovery in 2024, indicating that green consciousness has established substantial stability and long-term effect in household decision-making. In the meantime, the frequency of education factors steadily declines, likely reflecting that as solar PV information becomes more widely available, education plays a less important role as an adoption motivator due to lower information acquisition costs [17].

	2021	2022	2023	2024
age	185	86	96	83
cost	1069	1919	44	66
economic benefits	574	68	50	65
education	79	10	3	1
electricity prices	1	251	425	484
energy consumption	694	7	18	17
environmental motivation	42	59	73	260
financial capacity	173	215	97	108
house age	649	486	491	719
household composition	319	163	296	325
housing type	2760	2575	2374	2503
installation process	3788	3534	3484	3406
livable area	176	11	35	17
neighborhood effects	1888	2866	2527	2627
others	805	587	671	667
policy incentive	26	1	36	40
policy regulation	704	401	354	598
technical attitude	1	0	0	0

Figure 6-12 Frequency of barriers mentioned in each year

Regarding barriers, installation process, dwelling types, and neighborhood influences consistently constitute the most critical obstacles (Figure 6-12). This reveals persistent challenges in physical conditions and installation coordination, where policy and market interventions have not yet achieved obvious improvements. Particularly, the frequency of neighborhood effects mentioned as barriers has increased significantly since 2022. This may be because coordination and consensus issues among households in multi-story apartments became ever more apparent as non-apartment residential properties approached saturation, highlighting the social complexity of the technology implementation process.

Cost barriers, on the other hand, are most noticeable in 2021 and 2022. They are particularly highlighted in 2022 due to supply chain instabilities, and then quickly decrease thereafter. In parallel, the constraining effect of financial barriers declines. This reflects the combined impact of market maturation, declining installation costs, and enhanced policy incentives, which collectively lower the economic threshold for adoption and improve the perceived value proposition of solar PV systems [18].

In conclusion, while solar PV adoption motivations and barriers show certain stability over time, their relative importance gradually shifts. From the initial motivation dominated by financial capacity and economic benefits, it has gradually shifted toward a more diversified model that emphasizes policy incentives and environmental motivation more strongly. At the same time, the influence of cost as core barriers has significantly weakened, while structural constraints (such as installation procedures, dwelling types, and neighborhood coordination) continue to be key obstacles across time periods, reflecting the persistence of physical and social coordination problems. This evolution suggests that it is necessary to expand the focus of policy intervention from purely economic incentives to more systematic strategy combinations.

6.3 Insights and Implications

This section summarizes the key findings and their practical implications, building on the previous analysis of solar PV adoption patterns, motives, and barriers.

6.3.1 Key Insights

Transformation of adoption motives: The research finds that the driving factors for solar adoption are undergoing a transformation from economic rationality to multi-dimensional value. Although financial capacity and economic benefits are significant, their relative importance is progressively diminishing as environmental values and policy incentives have consistent or increasing impact. This change reflects the evolution of adopter composition during the technology diffusion process, namely the transition from early economically-oriented adopters to value-oriented adopters [3], [19], [20]. This finding indicates the need to shift from economic incentives toward comprehensive incentive systems.

Persistence of Structural Barriers: The study reveals that structural obstacles remain universally prevalent across different time periods and demographic groups. Barriers including installation process complexity, dwelling type limitations, and collective decision-making challenges in multi-unit housing consistently appear with high frequency. These hurdles are more likely to be caused by shortcomings in institutional mechanisms than by technological feasibility or economic affordability. For example, in multi-story housing, as pointed out by Kraaijvanger et al.[5], the collective decision-making complexity faced by homeowners' associations (VvE) constitutes the main institutional barrier to adoption. This finding underscores the crucial importance of institutional innovation in facilitating technology diffusion.

Disaggregated Effects of Socio-Demographic Heterogeneity: The research further shows that solar adoption decisions exhibit significant group heterogeneity, with residents of different income levels and dwelling types experiencing distinct motivational drivers and constraints. High-income households typically possess stronger financial capacity and decision-making autonomy, responding more positively to external signals such as policy incentives and social influences. Conversely, middle- and low-income groups living in multi-unit housing are more likely to be limited by concerns such as financial constraints, low neighborhood adoption rates, and lack of negotiation mechanisms, making it difficult for adoption intentions to successfully translate into actual behavior. This insight indicates that promoting solar adoption requires designing differentiated tools for different group characteristics, as uniform policy models cannot effectively cover the needs of heterogeneous groups.

6.3.2 Policy Implications

Based on the above insights, this study proposes the three primary principles for future residential solar PV promotion: comprehensive strategic framework, institutional innovation for structural barriers and differentiated strategies to address group heterogeneity. To be specific, the following are some practical recommendations:

1) **Transition from economic to comprehensive incentives:** With the transformation of adoption motivation structure, policy focus should shift from purely economic incentives to comprehensive incentive frameworks addressing environmental values, process facilitation, and social influences. For example, this could include community education programs highlighting solar energy's environmental benefits [21].
2) **Balance social equity with energy transition:** Solar policy design should prioritize energy justice, ensuring that the energy transition does not worsen existing social inequalities. This requires incorporating distributional effect analysis in policy evaluation and implementing targeted support to guarantee participation opportunities for vulnerable groups.
3) **Collective adoption support system:** To address collective decision-making dilemmas in apartment housing, establishing specialized institutional arrangements to reduce coordination costs is essential. Drawing on suggestions from Kraaijvanger et al. [5], specific measures include: establishing simplified approval processes and one-stop service platforms for solar projects for homeowners' associations; providing public

funding for preliminary feasibility studies, technical consulting, and legal support; and offering innovative frameworks for benefit distribution and property rights allocation, including rooftop space sharing mechanisms and insurance arrangements.

4) **Process standardization and optimization:** To overcome the universal barrier of complexity and uncertainty in installation process, communication costs can be minimized if the process becomes more apparent through institutional innovation. This involves developing unified solar installation application platforms that include permit approval, technical evaluation, and construction management. The standardized installation and approval processes can also assist in reducing technical uncertainty and quality issues.
5) **Differentiated financial tools:** Based on findings of group heterogeneity, distinct financial incentive policies are worth implementing. For example, a solution is to provide low-interest loans and installation subsidies for middle- and low-income households, while offering tax benefits and expedited depreciation for higher-income groups. This solution attempts to enhance social inclusion in the solar energy transition while avoiding increasing existing social inequalities [22].
6) **Spatially targeted policy design:** It is important to implement differentiated policies based on regional characteristics [23], which means policymakers should identify different types of neighborhoods and develop appropriate plans. In neighborhoods with high owner-occupancy rates but low installation rates, authorities can investigate the underlying causes and provide targeted financial and institutional support. For densely populated areas with multi-unit housing, addressing cooperative decision-making and coordination costs through institutional innovation proves beneficial.
7) **Neighborhood-level intervention strategies**: Based on neighborhood effect considerations, it is recommended to apply community-level intervention measures. Drawing on findings regarding spatial interaction effects [8], specific measures could include establishing solar demonstration blocks to increase technology visibility, assisting in the formation of localized solar cooperative organizations to promote knowledge dissemination and experience exchange, and establishing community energy advisor systems to provide ongoing technical support.

In conclusion, this study's analysis of solar adoption behavior and the potential policy recommendations provide important insights for understanding household behavior in urban energy transition, providing an empirical foundation and specific implementation pathways for solar policy optimization in Amsterdam and similar cities. The effective implementation of these recommendations requires multi-departmental coordination and long-term commitment, aimed at addressing key bottlenecks in current solar promotion and drive cities toward more equitable and sustainable energy system transitions.

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Chapter 7 Discussion

In the previous chapters, we developed PVAgent, an LLM-based agent model, to simulate household decision-making about residential PV adoption and analyzed the insights gained from its outputs. This chapter will critically discuss the advantages and limitations of this approach, while exploring the potential for further research and practical application.

7.1 Strengths of the LLM-based Agent Model Approach

In this study, the LLM-based agent model demonstrated several advantages in simulating households' solar adoption, which have been discussed in the theoretical literature (see Chapter 2) and are also reflected in the specific application of this project.

First is its advanced reasoning and decision-making capability. Traditional agent-based modeling relies primarily on predefined rules, which presents significant limitations when simulating complex, ambiguous, and uncertain scenarios in the real world [1], [2]. In this study, LLM agents can automatically understand complex information about households' living conditions and social relationships through natural language prompts, then generate decisions with reasonable explanations. This flexible reasoning process not only improves the agents' human-likeness but also avoids subjective biases introduced by manually setting rules.

Second, LLM agents have remarkable knowledge integration and transfer capability. Through pre-training on large-scale datasets, LLMs possess extensive social and technological knowledge [3], [4]. In this study, without any specialized training, the model could automatically simulate household decisions based on simple input information and identify relevant barriers or motive factors. Its simulation results indicate the zero-shot generalization ability, which effectively helps address challenges posed by missing data or modeling complexity.

Additionally, the interpretability of generative output represents another significant advantage. Unlike traditional statistical and machine learning methods that produce only structured behaviors (such as "adopt/not adopt"), LLM agents can generate decision rationales in natural language form [5]. This interpretability greatly enhances the analytical dimensions of the simulation. In this study, these textual data were not only used as behavioral judgments but also served as material for further thematic analysis and policy insights. For example, by analyzing the generated reasoning text, we can extract main barriers and motivation as well as their distribution characteristics. This is helpful for understanding the complex considerations during decision-making processes.

Meanwhile, scalability and reusability also provide convenience for broader application scenarios [4], [6]. The LLM-based agent model features a simple structure and flexible prompts, it easily extensible to other simulation contexts. Simulations about different regional or policy settings require only updating input information and prompts, without reconstructing the model mechanism. This gives this approach good adaptability for further application. For example, in the future, the impact of subsidy policies or promotional measures on behavioral changes can be quickly simulated through prompt modifications.

In conclusion, the LLM-based agent model shows advanced capacity in this research. It provides a new tool for understanding complex adoption behaviors. However, it must be realized that this approach is still in its early stages, and its application comes with several limitations and challenges. The next section will further explore these limitations and their potential impact on research results.

7.2 Limitations of the LLM-Based Agent Model

Although the LLM-based agent modeling approach performs well in this study, it still has a couple of limitations. These issues result from the characteristics of current LLM technology itself and from specific challenges encountered in the actual simulation process.

First of all, the challenges commonly faced by AI and LLMs also apply here. One is the limitation of computational efficiency and resources. Although LLM-based agents have somewhat lowered the threshold for rule design compared to traditional ABM, it requires higher computational resources, especially when incorporating external knowledge retrieval, multi-round reasoning, or multi-agent system extensions. In this study, considering resource constraints, we controlled the number of agents and their interaction complexity. This compromise to some extent limited the model's scalability to larger scenarios. Second, safety, ethics, and human-machine boundary issues cannot be ignored [7]. Throughout the research design process, we consistently adhered to ethical and safety boundaries, but it cannot be overlooked that LLM models may always face issues such as privacy leaks, prompt manipulation, and training data bias in practice [1]. Especially when simulating sensitive just topics, the social impact and potential misleading risks of the results cannot be ignored. This also suggests that future applications of LLM-based agents need to be built on more transparent and controllable architectures, and require the establishment of more reasonable human-machine collaboration[2].

Second is the uncertainty and sensitivity of output. Although LLMs have powerful language understanding and generation ability, their generation process involves a certain degree of uncertainty [8], and outputs heavily depend on input information and prompt design. In this study, even though we set temperature to 0 for maximum reproducibility, the model's outputs at the individual level still showed slight fluctuations. While results at the macro level (such as regional overall adoption rates) showed certain stability, at the micro-individual level, inconsistent behavioral choices might still occur between different experiments, causing interference for fine-grained analysis. In addition, during the modeling process, we observed that the similar semantic content could lead to different model responses simply due to minor changes in prompt wording. This prompt sensitivity has been widely discussed in existing literature [9], [10]. It not only increases subjectivity in the modeling process but also poses challenges to model reproducibility in simulation. A standardized way of documenting the model development and implementation like the ODD protocol in ABM may help to enhance methodological transparency across LLM-based simulation studies [11].

Third, LLMs are susceptible to hallucination and may generate incorrect or misleading information [7], [12]. During the modeling process in this study, we noticed that LLM agents sometimes generate seemingly reasonable but factually unsupported information without clear basis. For example, some agents would mention reasons like "lengthy installation process" or "neighborhood opposition" when talking about their motivations and barriers. However, this kind of content was not explicitly provided in the prompts nor set as variables in the simulation environment. Such generation might reflect LLM's analogy to real-world experiences, but it could also be a typical hallucination phenomenon, generating statements inconsistent with factual data and input information [13]. For example, when several agents present similar but non-predetermined barrier reasons, researchers may misinterpret them for common barriers influenced by general circumstances or social dynamics, reducing the usefulness of the study's findings. Therefore, the results should be interpreted with caution and need to be always validated and calibrated.

The depth of cognitive and social behavior simulation is currently limited. Although current LLMs can simulate human language expression, they still lack genuine human consciousness structures and psychological mechanisms [7]. Without self-awareness and true situational perception, they struggle to authentically reproduce individual decisions under uncertain, ambiguous, or conflicting situations. In this study, despite guiding agents through prompt design to consider non-rational factors such as emotions, uncertainty, and risk preference, their decision-making process remains based on language pattern fitting and probabilistic generation. For example, behaviors like hesitation or conformity shown by individuals in simulations may not appear consistently across repeated experiments, suggesting these behaviors are immediate responses to input contexts rather than being driven by internal psychological variables. Therefore, while LLM agents demonstrate certain decision simulation capabilities, they still have obvious limitations in simulating complex human psychological mechanisms and long-term behavioral evolution.

Additionally, knowledge boundaries also pose challenges. LLM's knowledge foundation comes from existing training datasets, meaning it responds slowly to recent social changes, policy adjustments, or technological updates [14]. This makes it difficult to dynamically adapt to rapidly changing external environments. Meanwhile, LLM's knowledge retrieval mainly depends on the activation capability of input information [2]. If prompts fail to precisely guide the retrieval of relevant knowledge, the model's output may remain overly generalized. In this study, we found that some agent judgments could not adequately reflect details of recent solar energy promotion policies in the Netherlands or Amsterdam region, even though we provided hints in the input. All these factors indicate that while LLM agents show broad potential, they still require fine-designed external knowledge systems, stronger validation mechanisms, and ongoing awareness of their inherent uncertainties.

7.3 Reflection and Future Recommendation

Although this study successfully implemented simulation of household's solar energy adoption with an LLM-based agent model and obtained certain valuable insights, some limitations should be acknowledged. First, the factor framework derived from literature spanning 2015-2023 may inevitably overlook influential factors that have emerged more recently. Second, limited by the quantity and quality of available household-level micro data, this study used synthetic population as inputs. That may affect the comprehensiveness and accuracy of simulation results. Also, when inputting policy and program information, we may not have exhaustively covered all relevant policies, and the granularity of information provided to the agent was potentially limited. Additionally, translating Dutch policy documents and contextual information into English may have introduced interpretation biases that affect simulation accuracy.

Moreover, several methodological limitations affected the study's rigor. Despite multiple rounds of prompt design and adjustment, the prompt development process may still carry strong subjectivity, and it is difficult to determine whether the adopted prompts were optimal. Furthermore, the lack of systematic sensitivity analysis limited deep understanding of model stability and parameter influences. Finally, due to time and resource constraints, this study could not conduct in-depth comparisons between model reasoning results and actual household decision-making processes through methods such as interviews, which to some extent limited the credibility and real-world alignment of the model's reasoning outputs.

Therefore, future studies should improve data collection and model development process. This includes automated or semi-automated prompt optimization techniques to reduce subjective design bias [15]. Additionally, comprehensive sensitivity and robustness analyses should be conducted to ensure the model stability. Comparative validation between model reasoning results and real-world behaviors should be strengthened by collecting actual household decision-making logic and motivations through interviews, surveys, or workshops, in order to enhance the model's real-world alignment and explanatory power.

To further improve the model’s capabilities, future work could consider introducing Retrieval-Augmented Generation (RAG) technology [15] or combining hybrid approaches with structured knowledge bases and symbolic logic. That may help to address the limitations of pure language input. For example, in solar PV adoption simulation, incorporating structured information such as policy documents and technical manuals may improve the model's understanding of specific technical and policy details to reduce hallucination.

The practical application scenarios of this method can be further investigated as well. LLM-based agent model could assist public participation and collaborative decision-making in energy policy formulation with its advanced capacity in multi-agent interaction [8]. By simulating the perspectives and dynamics of different stakeholders, they can support the design of more inclusive intervention. For instance, it can be used to simulate the interaction within housing associations to further understand the mechanism of collective decision-making for households living in apartments.

Finally, for future similar research, strengthening the transparency and ethical standards of simulation studies and establishing standardized reproducible reporting processes are fundamental to ensuring scientific rigor and social responsibility. In this case, making prompt designs, model parameters, and data sources publicly available is necessary to facilitate peer verification and accelerate methodological progress. Also, interdisciplinary collaboration between experts from social sciences, computer science, and energy fields, will be essential for developing more comprehensive and accurate social behavior simulations that inform innovative policy-making and practical applications.

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Chapter 8 Conclusion

Residential solar photovoltaic (PV) systems play an important role in energy transition as well as in addressing climate change and energy security issues. Particularly in urban areas, solar energy adoption not only brings environmental benefits but also creates economic value for residents. However, the adoption of solar PV exhibits pronounced social disparities, with some socioeconomically disadvantaged households facing greater barriers to adoption, raising widespread concerns about energy equity. Understanding the decision-making process of household solar adoption enables a deeper understanding of the barriers faced by different groups and identification of deficiencies in existing policies, which is crucial for promoting equitable adoption and achieving better environmental outcomes.

Although there has been extensive research exploring the motivating factors and barriers affecting solar adoption, understanding of how these factors dynamically operate within household decision and behavior remains limited. One of the reasons is existing methods struggle to simulate complex decision-making mechanisms. Large Language Models (LLMs), with their powerful natural language processing and generation capabilities, demonstrate human-like environmental perception and reasoning characteristics. That makes LLM-based agents possess the potential to integrate multi-source information and conduct complex reasoning without explicit rules, as well as support linguistic interactions between agents. This provides new opportunities for simulating and understanding households’ energy decision-making behavior.

Therefore, this study aims to explore the feasibility and development of LLM-based agent models in solar adoption decision-making modeling. We expect to provide insights for achieving a more equitable energy transition. We developed an LLM-based agent framework named PVAgent that integrates socioeconomic characteristics, neighborhood connection and policy variables. This framework is used to simulate households' reasoning processes when deciding whether to adopt solar PV systems.

In the first phase, we reviewed 65 relevant papers to identify the multidimensional factors influencing household solar PV system adoption. Based on this review and relevant decision-making theories, we developed a conceptual framework. This framework divides influencing factors into four categories: technical attributes (such as installation costs and system efficiency), household and individual characteristics (such as income level, educational background, and homeownership), personal beliefs and intentions (including attitudes toward solar energy, environmental values, and adoption intentions), and external contexts (such as the physical environment, policy incentives, and social networks). We not only summarized the important features within each category, but also highlighted possible complicated connections between them. We also found that the importance and influence of factors may change across different stages of technology adoption. This serves as a theoretical foundation and input structure reference for future modeling.

In the second phase, we focused on constructing and developing the LLM-based agent model (PVAgent). We transformed the key influencing factors and typical household decision-making scenarios summarized in the first stage into structured inputs. Combined with the general framework and conversational capabilities of LLM-based agents, we designed an agent system capable of simulating the solar adoption decision-making process. Model development involved two steps. The first step was based on static population samples and primarily simulated the influence of individual-level characteristics (such as income, environmental attitudes, and policy exposure) and external variables on solar adoption behavior. By encoding these variables as natural language prompts, the model could generate explanatory human language outputs. These outputs reflected the judgment logic behind household adoption decisions and their underlying motivations. Building on this foundation, the model further introduced neighborhood structures and temporal dynamics. We therefore constructed a multi-agent system with multi-year evolution capabilities. This system simulates how social influence gradually spreads in neighborhood relationships and affects household behavioral changes. This mechanism allows the model to move beyond static judgment toward behavioral evolution and trend formation. Through manual review and trend comparison with real-world data, results showed that the model could generate reasonable behavioral logic and motivation at the individual level. At the group level, it also demonstrated structural characteristics and diffusion dynamics consistent with reality.

In the third phase, we conducted simulation analysis of household solar adoption decision in three representative neighborhoods in Amsterdam: Oude Pijp, Slotervaart-Noord, and Omval/Overamstel. We used the completed LLM agent model and focused on exploring behavioral evolution and driving factors across different social groups and spatial dimensions. We discovered a transition from economic rationality to multi-dimensional values by examining the agents' adoption decisions and reasons. We also identified important stratification mechanisms that impact equitable adoption and highlighted the institutional foundations of structural barriers. These insights reveal the structural challenges faced in promoting equitable energy transition and provide a foundation for designing targeted policy interventions. Based on these findings, the study further recommends that future policies should shift from single economic incentives to comprehensive intervention strategies. Policies should encourage institutional innovation and provide unique solutions for distinct populations. In order to accomplish a more sustainable and equitable energy transition, they should also consider dynamic methods at the neighborhood level.

This study integrates LLMs into energy transition decision-making models with the three-stage research approach mentioned above. We constructed and validated a household agent model with contextual reasoning capabilities. The model simulates household adoption decisions for solar PV in urban neighborhoods. This approach provides new tools for agent-based modeling and understanding complex social decision-making behavior.

However, this study has several limitations. First, the available data has limited coverage and lacks sufficient detail. This constrains the model's input precision and its ability to fully capture real-world heterogeneity and dynamic changes. Second, the prompt design process involves some subjectivity. Model outputs' repeatability is impacted by their sensitivity to verbal suggestions. Third, the lack of systematic sensitivity analysis and field validation limits comprehensive assessment of model stability and authenticity. Future research could combine user interviews and behavioral surveys to enhance comparison between the model and real decision-making mechanisms.

In future, the LLM-based agent modeling approach will have potential at both theoretical and practical levels. Methodologically, this approach can be further enhanced by integrating Retrieval-Augmented Generation (RAG) technology or structured knowledge bases. By doing this, the model would be better equipped to handle factual and time-sensitive data, which would enable it to be used in more complicated situations. In practice, LLM agents can support energy policymaking, public participation simulation, and intervention design. They provide contextual awareness and interactive tools for urban energy transition. In the meantime, appropriate use of this approach requires advanced ethical frameworks, reporting requirements, and research transparency. In order to further the theoretical development and application of this approach, interdisciplinary collaboration will be essential.

In conclusion, this research provides a new perspective for understanding household decision making in solar PV adoption processes by introducing LLM-based agent modeling approach. It also provides theoretical foundations and methods for future research and policy interventions to achieve just energy transition.

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Appendix A Context Information

Table A-1 The price of solar panels per year.

Source: Milieu Centraal, "Kosten en opbrengst zonnepanelen," *MilieuCentraal.nl*, juli 2024 [Online]. Available: https://www.milieucentraal.nl/energie-besparen/zonnepanelen/kosten-en-opbrengst-zonnepanelen/ (accessed May. 11, 2025)

Year	Price per Watt peak
2020	1.26 euros
2021	1.20 euros
2022	1.83 euros
2023	1.24 euros
2024	0.90 euros

Table A-2 Solar PV payback period and savings

Source: Hoek's T Installaties, "Kosten en opbrengst zonnepanelen – Terugverdientijd," *hoekstrainstallaties.nl*, 2021. [Online]. Available: https://www.hoekstrainstallaties.nl/zonnepanelen-amsterdam/#terugverdientijd (accessed May. 11, 2025).

"On average, people earn back the cost of solar panels within **eight to nine years**. They have the right number of panels installed to make their savings as optimal as possible. For example, the average household of one person has **eight solar panels** installed. This costs about **€4,000** and yields **€497** per year. Then you will have earned back the solar panels within **nine** years."

Table A-3 Electricity price for household in the Netherlands

Source: Centraal Bureau voor de Statistiek (CBS), "Eindverbruikersprijzen aardgas en elektriciteit," StatLine, gewijzigd op 28 maart 2025. [Online]. Available: https://opendata.cbs.nl/statline/?dl=97843#/CBS/nl/dataset/85666NED/table (accessed op May. 11, 2025)

Year	Electricity price (household consumption classes: 2.5 to 5 MWh)
2020	0.142 euros per KWh
2021	0.136 euros per KWh
2022	0.105 euros per KWh
2023	0.317 euros per KWh
2024	0.243 euros per KWh

Table A-4 National and local regulation and incentives

Catalog	Level	Source
Subsidy for solar panels	National	Rijksoverheid, "Krijg ik subsidie voor zonnepanelen?", *Rijksoverheid.nl*, bijgewerkt 2025. [Online]. Available: https://www.rijksoverheid.nl/onderwerpen/energie-thuis/vraag-en-antwoord/krijg-ik-subsidie-voor-zonnepanelen (accessed May. 11, 2025)
No VAT on solar panels since 2023	National	Milieu Centraal, "Btw en zonnepanelen," *MilieuCentraal.nl*, vanaf 1 jan. 2023 is het btw-tarief 0 %. [Online]. Available: https://www.milieucentraal.nl/energie-besparen/zonnepanelen/btw-en-zonnepanelen/ (accessed May. 19, 2025)
Salderingsregeling (net metering scheme)	National	F. Verheij, M. Menkveld, and O. Usmani, "Effect afbouw salderingsregeling op de terugverdientijd van investeringen in zonnepanelen," *TNO-rapport P11928, Ministerie van Economische Zaken en Klimaat*, Mar. 25, 2020. [Online]. Available: https://www.rijksoverheid.nl/documenten/rapporten/2020/03/25/bijlage-effect-afbouw-salderingsregeling-op-de-terugverdientijd-van-investeringen-in-zonnepanelen (accessed May. 19, 2025).
Solar panels: conditions for permit-free installation	National	Informatiepunt Leefomgeving (IPLO), "Zonnepanelen: voorwaarden vergunningvrij plaatsen," *IPLO.nl*, [Online]. Available: https://iplo.nl/thema/toepassing-regels-praktijk/zonnepanelen/plaatsen/voorwaarden-vergunningvrij-plaatsen/ (accessed May. 19, 2025).
Group decision-making on solar energy in (home) owners' associations	National	J. C. M. Roodenrijs, D. L. T. Hegger, H. L. P. Mees, and P. Driessen, 'Opening up the Black Box of Group Decision-Making on Solar Energy: The Case of Strata Buildings in Amsterdam, the Netherlands', *Sustainability*, vol. 12, no. 5, p. 2097, Mar. 2020, doi: 10.3390/su12052097.
Subsidy for Sustainable Amsterdam energy for special solar panels	Local	Gemeente Amsterdam, "Subsidie duurzame Amsterdamse energie – bijzondere zonnepanelen," *Amsterdam.nl,* gewijzigd 16 juli 2024 (bijgewerkt t/m heden). [Online]. Available: https://www.amsterdam.nl/subsidies/subsidieregelingen/subsidie-duurzame-amsterdamse-energie/#h39319133-b335-4f27-b129-eb6d39704a6c (accessed May. 11, 2025)

Appendix B

Table B-1 Full list of the reviewed papers for factor analysis in Chapter 4

No	Author(s)	Year	Title	Location	Source
1	Solangi et al.	2015	Social acceptance of solar energy in Malaysia: users' perspective	Malaysia	Clean Technologies and Environmental Policy
2	Agarwal et al.	2015	A model for residential adoption of photovoltaic systems	US	2015 IEEE Power & Energy Society General Meeting
3	Bauner & Crago	2015	Adoption of residential solar power under uncertainty: Implications for renewable energy incentives	US	Energy Policy
4	Vasseur & Kemp	2015	A segmentation analysis: the case of photovoltaic in the Netherlands	Netherlands	Energy Efficiency
5	Schaffer & Brun	2015	Beyond the sun—Socioeconomic drivers of the adoption of small-scale photovoltaic installations in Germany	Germany	Energy Research & Social Science
6	Balta-Ozkan et al.	2015	Regional distribution of photovoltaic deployment in the UK and its determinants: A spatial econometric approach	UK	Energy Economics
7	Rai & Beck	2015	Public perceptions and information gaps in solar energy in Texas	US	Environmental Research Letters
8	Yamamoto	2015	Opinion leadership and willingness to pay for residential photovoltaic systems	Japan	Energy Policy
9	Karakaya et al.	2015	Motivators for adoption of photovoltaic systems at grid parity: A case study from Southern Germany	Germany	Renewable and Sustainable Energy Reviews

No	Author(s)	Year	Title	Location	Source
10	Palmer et al.	2015	Modeling the diffusion of residential photovoltaic systems in Italy: An agent-based simulation	Italy	Technological Forecasting and Social Change
11	Korcaj et al.	2015	Intentions to adopt photovoltaic systems depend on homeowners' expected personal gains and behavior of peers	Germany	Renewable Energy
12	Sigrin et al.	2015	Diffusion into new markets: evolving customer segments in the solar photovoltaics market	US	Environmental Research Letters
13	Robinson & Rai	2015	Determinants of spatio-temporal patterns of energy technology adoption: An agent-based modeling approach	US	Applied Energy
14	Vasseur & Kemp	2015	The adoption of PV in the Netherlands: A statistical analysis of adoption factors	Netherlands	Renewable and Sustainable Energy Reviews
15	Yun & Lee	2015	Advancing societal readiness toward renewable energy system adoption with a socio-technical perspective	US	Technological Forecasting and Social Change
16	Rai & Robinson	2015	Agent-based modeling of energy technology adoption: Empirical integration of social, behavioral, economic, and environmental factors	US	Environmental Modelling & Software
17	Graziano & Gillingham	2015	Spatial patterns of solar photovoltaic system adoption: The influence of neighbors and the built environment	US	Journal of Economic Geography
18	Palm	2016	Local factors driving the diffusion of solar photovoltaics in Sweden: A case study of five municipalities in an early market	Sweden	Energy Research & Social Science
19	Rai et al.	2016	Overcoming barriers and uncertainties in the adoption of residential solar PV	US	Renewable Energy
20	De Groote et al.	2016	Heterogeneity in the adoption of photovoltaic systems in Flanders	Belgium	Energy Economics
21	Khalil et al.	2017	Solar PV adoption for homes (A case of Peshawar, Pakistan)	Pakistan	2017 International Symposium on Recent Advances in Electrical Engineering (RAEE)

No	Author(s)	Year	Title	Location	Source
22	Briguglio & Formosa	2017	When households go solar: Determinants of uptake of a Photovoltaic Scheme and policy insights	Malta	Energy Policy
23	Simpson & Clifton	2017	Testing Diffusion of Innovations Theory with data: Financial incentives, early adopters, and distributed solar energy in Australia	Australia	Energy Research & Social Science
24	Kausika et al.	2017	Assessment of policy based residential solar PV potential using GIS-based multicriteria decision analysis: A case study of Apeldoorn, The Netherlands	NL	Energy Procedia
25	Sommerfeld et al.	2017	Influence of demographic variables on uptake of domestic solar photovoltaic technology	Australia	Renewable and Sustainable Energy Reviews
26	Dharshing	2017	Household dynamics of technology adoption: A spatial econometric analysis of residential solar photovoltaic (PV) systems in Germany	Germany	Energy Research & Social Science
27	Wolske et al.	2017	Explaining interest in adopting residential solar photovoltaic systems in the United States: Toward an integration of behavioral theories	US	Energy Research & Social Science
28	Reeves et al.	2017	Evolution of consumer information preferences with market maturity in solar PV adoption	US	Environmental Research Letters
29	Crago & Chernyakhovskiy	2017	Are policy incentives for solar power effective? Evidence from residential installations in the Northeast	US	Journal of Environmental Economics and Management
30	Abdullah et al.	2017	Acceptance and willingness to pay for solar home system: Survey evidence from northern area of Pakistan	Pakistan	Energy Reports
31	Dos Santos et al.	2018	Projection of the diffusion of photovoltaic systems in residential low voltage consumers	Brazil	Renewable Energy
32	Lin et al.	2018	The Influence of Local Environmental, Economic and Social Variables on the Spatial Distribution of Photovoltaic Applications across China's Urban Areas	China	Energies

No	Author(s)	Year	Title	Location	Source
33	Parkins et al.	2018	Predicting intention to adopt solar technology in Canada: The role of knowledge, public engagement, and visibility	Canada	Energy Policy
34	Kesari et al.	2018	Consumer Purchasing Behaviour towards Eco-Environment Residential Photovoltaic Solar Lighting Systems	India	Global Business Review
35	Rahut et al.	2018	The use and determinants of solar energy by Sub-Saharan African households	Sub-Saharan African	International Journal of Sustainable Energy
36	Bondio et al.	2018	The technology of the middle class: Understanding the fulfilment of adoption intentions in Queensland's rapid uptake residential solar photovoltaics market	Australia	Renewable and Sustainable Energy Reviews
37	Walters et al.	2018	A Systems Analysis of Factors Influencing Household Solar PV Adoption in Santiago, Chile	Chile	Sustainability
38	Jayaweera et al.	2018	Local factors affecting the spatial diffusion of residential photovoltaic adoption in Sri Lanka	Sri Lanka	Energy Policy
39	Palm	2018	Household installation of solar panels – Motives and barriers in a 10-year perspective	Sweden	Energy Policy
40	Kowalska-Pyzalska	2018	An Empirical Analysis of Green Electricity Adoption Among Residential Consumers in Poland	Poland	Sustainability
41	Van Der Kam et al.	2018	Diffusion of solar photovoltaic systems and electric vehicles among Dutch consumers: Implications for the energy transition	Netherlands	Energy Research & Social Science
42	Bashiri & Alizadeh	2018	The analysis of demographics, environmental and knowledge factors affecting prospective residential PV system adoption: A study in Tehran	Iran	Renewable and Sustainable Energy Reviews
43	Zander et al.	2019	Preferences for and potential impacts of financial incentives to install residential rooftop solar photovoltaic systems in Australia	Australia	Journal of Cleaner Production

No	Author(s)	Year	Title	Location	Source
44	Best et al.	2019	Understanding the determinants of rooftop solar installation: evidence from household surveys in Australia	Australia	Australian Journal of Agricultural and Resource Economics
45	Petrovich et al.	2019	Beauty and the budget: A segmentation of residential solar adopters	Swiss	Ecological Economics
46	Jacksohn et al.	2019	Drivers of renewable technology adoption in the household sector	Germany	Energy Economics
47	Lukanov & Krieger	2019	Distributed solar and environmental justice: Exploring the demographic and socio-economic trends of residential PV adoption in California	US	Energy Policy
48	Poruschi & Ambrey	2019	Energy justice, the built environment, and solar photovoltaic (PV) energy transitions in urban Australia: A dynamic panel data analysis	Australia	Energy Research & Social Science
49	Lee & Hong	2019	Hybrid agent-based modeling of rooftop solar photovoltaic adoption by integrating the geographic information system and data mining technique	Korea	Energy Conversion and Management
50	Sun et al.	2020	Consumer attitude and purchase intention toward rooftop photovoltaic installation: The roles of personal trait, psychological benefit, and government incentives	China	Energy & Environment
51	Cherry & Sæle	2020	Residential Photovoltaic Systems in Norway: Household Knowledge, Preferences and Willingness to Pay	Norway	Challenges in Sustainability
52	Jan et al.	2020	Social acceptability of solar photovoltaic system in Pakistan: Key determinants and policy implications	Pakistan	Journal of Cleaner Production
53	Parsad et al.	2020	A study on the factors affecting household solar adoption in Kerala, India	India	International Journal of Productivity and Performance Management
54	Wolske	2020	More alike than different: Profiles of high-income and low-income rooftop solar adopters in the United States	US	Energy Research & Social Science

No	Author(s)	Year	Title	Location	Source
55	Niamir et al.	2020	Demand-side solutions for climate mitigation: Bottom-up drivers of household energy behavior change in the Netherlands and Spain	Netherlands, Spain	Energy Research & Social Science
56	Reames	2020	Distributional disparities in residential rooftop solar potential and penetration in four cities in the United States	US	Energy Research & Social Science
57	Mundaca & Samahita	2020	What drives home solar PV uptake? Subsidies, peer effects and visibility in Sweden	Sweden	Energy Research & Social Science
58	De Freitas	2022	What's driving solar energy adoption in Brazil? Exploring settlement patterns of place and space	Brazil	Energy Research & Social Science
59	Best	2022	Energy inequity variation across contexts	US	Applied Energy
60	Gao & Zhou	2022	Solar adoption inequality in the U.S.: Trend, magnitude, and solar justice policies	US	Energy Policy
61	Ruokamo et al.	2023	Innovators, followers and laggards in home solar PV: Factors driving diffusion in Finland	Finland	Energy Research & Social Science
62	Zhang et al.	2023	Neighbourhood-level spatial determinants of residential solar photovoltaic adoption in the Netherlands	Netherlands	Renewable Energy
63	Min et al.	2023	Clean energy justice: Different adoption characteristics of underserved communities in rooftop solar and electric vehicle chargers in Seattle	US	Energy Research & Social Science
64	Kraaijvanger et al.	2023	Does the sun shine for all? Revealing socio-spatial inequalities in the transition to solar energy in The Hague, The Netherlands	Netherlands	Energy Research & Social Science
65	Zhang et al.	2023	Regional disparity of residential solar panel diffusion in Australia: The roles of socio-economic factors	Australia	Renewable Energy

Appendix C

C-1 Code for Phase 1

```
import pandas as pd
import openai
import json
import time
# ==================== Initialization ====================
api_key = "API KEY"
# ==================== Configuration and Metadata ====================

USED_FIELDS = [
    "id", "age", "education", "hh_size", "hh_comp", "income",
    "wealth", "ownership", "dwelling_type", "usable_area", "constr_year",
    "elect_cons", "gas_cons", "contact_neigh"
]

FIELD_DESCRIPTIONS = {
    "age": "Age of the household head",
    "education": "Education level of the household head",
    "hh_size": "Total number of people in the household",
    "hh_comp": "Household composition (e.g., adults/children)",
    "income": "Household income",
    "wealth": "Household wealth level",
    "ownership": "Homeownership status",
    "dwelling_type": "Type of dwelling (e.g., apartment or not)",
    "usable_area": "Usable floor area of the home",
    "constr_year": "Construction year of the home",
    "elect_cons": "Monthly electricity consumption",
    "gas_cons": "Monthly gas consumption",
    "contact_neigh": "Level of contact with neighbors"
}

EXTERNAL_INFO_2021 = {
    "Adoption context": (
        "Only around 7% of households in Amsterdam had installed rooftop solar
           or heat pump systems in 2021."
        "This means adoption was still relatively rare."
    ),
    "Financial factors": (
        "Expect to pay roughly €4,000 to €5,000 for 10 solar panels, excluding
           btw."
        "Annual savings could reach €497, and the estimated payback period was
           4 to 9 years, depending on usage."
    ),
    "Energy prices": (
        "Electricity cost €0.136 per kWh (for households using 2,500-5,000
           kWh/year)."
    ),
    "Installation access": (
        "Apartments often required coordination with neighbors or housing
           associations, but it is still possible."
    ),
```

```
    "Policy and legal environment": (
        "Some incentives were available for solar adoption, especially
           through housing associations. "
        "However, state-protected historic buildings (often older homes)
           required special permits for rooftop installations."
    )
}
```

```
# ============================== Data Processing ===============================

def load_and_preprocess_data(filepath: str, n: int = 60) -> pd.DataFrame:
    df = pd.read_csv(filepath)[USED_FIELDS].copy()
    df["house_age"] = 2021 - df["constr_year"]
    return df
```

```
# ============================ Prompt Construction ============================

def build_profile_paragraph(row: pd.Series) -> str:
    parts = []

    if pd.notnull(row["age"]):
        parts.append(f"You are aged {row['age']}")
    if pd.notnull(row["education"]):
        parts.append(f"with a {row['education']} level of education")

    if pd.notnull(row["ownership"]):
        own_text = "own" if row["ownership"] == "owner" else "rent"
        dwelling = row["dwelling_type"] if pd.notnull(row["dwelling_type"])
           else "dwelling"
        parts.append(f"and you {own_text} a {dwelling}")

    if pd.notnull(row["house_age"]):
        parts.append(f"built approximately {int(row['house_age'])} years ago")

    if pd.notnull(row["usable_area"]):
        parts.append(f"with {int(row['usable_area'])} square meters of usable
           area")

    if pd.notnull(row["hh_size"]):
        parts.append(f"You live with a household of {row['hh_size']} people")
    if pd.notnull(row["hh_comp"]):
        parts.append(f"and the composition is '{row['hh_comp']}'")

    if pd.notnull(row["income"]):
        parts.append(f"Your annual household income is €{int(row['income'])}")
    if pd.notnull(row["wealth"]):
        parts.append(f"and your reported wealth is €{int(row['wealth'])}")

    if pd.notnull(row["elect_cons"]):
        parts.append(f"You consume about {int(row['elect_cons'])} kWh of
           electricity per year")
    if pd.notnull(row["gas_cons"]) and row["gas_cons"] > 0:
        parts.append(f"and also use gas ({int(row['gas_cons'])} m³ per year)")

    if pd.notnull(row["contact_neigh"]):
        parts.append(f"You report '{row['contact_neigh']}' levels of contact
           with your neighbors")

    profile = " ".join(parts) + "."
    return profile
```

```python
def build_prompt(row: pd.Series) -> str:
    profile = build_profile_paragraph(row)
    return (
        "You are a household living in Amsterdam in the year 2021.\n"
        "Based on your household's situation and the policy environment at the
           time, think carefully about whether you have already installed
           rooftop solar panels—or whether you are genuinely and actively
           considering doing so.\n"
        "Consider your financial capacity, energy usage, social context, and
           environmental motivation and so on to see if there are strong
           .\n"
        "Also consider the complexities and frictions involved, such as your
           household size and energy demanding, social context, and the
           potential difficulties in coordinating installation.\n"
        "Even if solar panels seem financially beneficial in theory, many
          households delay or reject adoption due to hesitation, uncertainties,
           or competing priorities.\n"
        "Many families also have concerns about the process being complicated,
           time-consuming, or uncertain. While some may have strong
           environmental motivation or financial incentives, the real-world
           barriers to adoption can often outweigh these motivations.\n\n"
        f"Here is the contextual information as of
           2021:\n{EXTERNAL_INFO_2021}\n\n"
        f"Here is your household profile:\n{profile}\n\n"
        "Do not assume a yes or no decision based solely on your dwelling
           type."
        "Please respond in the following JSON format:\n"
        "{\n"
        '   "decision": "yes" or "no",\n'
        '   "reasoning": "A detailed explanation about your decision (2-3
           sentences)..."\n'
        "}"
    )
```

```python
# ============================== LLM Interaction ==============================

SYSTEM_MESSAGE = {
    "role": "system",
    "content": (
        "You are a household in Amsterdam in 2021 deciding whether to install
           rooftop solar panels.\n\n"
        "Adoption often occurs in diverse households—not just those with
           perfect housing conditions.\n\n"
        "Consider economic, behavioral, and situational factors, such as income,
           energy demands, trust in technology, household composition, roof
           access, and social norms.\n\n"
        "Your decision should reflect the real-world context, where most
           households do not act purely on financial logic—real-world decisions
           often involve hesitation, competing priorities, and behavioral
           friction.\n\n"
        "Households may also have different environmental attitude, political
           stance and investment propensity \n\n"
        "Most households do not act purely based on economic logic. It is
           common to hesitate or postpone installation due to doubts, inertia,
           lack of time, or concern about complexity.\n"
        "**Do not assume a yes or no decision based solely on dwelling type.**
           Some people living in 'non-apartment' also face with complexity,
           while many apartments have successfully installed panels when owners
           are proactive or feel connected to their community.\n\n"
        "Weigh all relevant factors fairly and realistically.\n"
        "Respond only in strict JSON format."
    )
}
```

```python
def query_llm(prompt: str) -> dict:
    try:
        messages = [SYSTEM_MESSAGE, {"role": "user", "content": prompt}]
        response = client.chat.completions.create(
            model="gpt-4o-mini",
            messages=messages,
            temperature=0,
            response_format={"type": "json_object"},
            top_p=1.0,
            frequency_penalty=0,
            presence_penalty=0,
        )
        content = response.choices[0].message.content.strip()
        print(f"Raw response content: {content[:100]}...")

        if content.startswith("```"):
            content_parts = content.split("```")
            if len(content_parts) > 1:
                content = content_parts[1].strip()
                if content.startswith("json"):
                    content = content[len("json"):].strip()

        try:
            return json.loads(content)
        except json.JSONDecodeError as json_err:
            print(f"JSON parsing error: {json_err}")
            print(f"Full content received:\n{content}")
            return {"decision": None, "reasoning": f"JSON parsing error:
           {str(json_err)}"}
    except Exception as e:
        print("LLM Error:", e)
        return {"decision": None, "reasoning": str(e)}
```

```python
# ================================ Main Logic ================================

def process_solar_adoption_decisions(input_file: str, output_file: str):
    df = load_and_preprocess_data(input_file)
    results = []

    for idx, row in df.iterrows():
        print(f"Processing household {idx + 1}/{len(df)}...")
        prompt = build_prompt(row)
        result = query_llm(prompt)
        results.append(result)
        time.sleep(1.2)

    df["llm_decision"] = [r["decision"] for r in results]
    df["llm_reasoning"] = [r["reasoning"] for r in results]

    df.to_csv(output_file, index=False)
    print(f"Done. Results saved in {output_file}")


# ==================== Execution ====================

if __name__ == "__main__":
    process_solar_adoption_decisions("250413_clean_owneronly.csv",
           "250517_test_all_2.csv")
```

C-2 Code for Phase 2

```python
import pandas as pd
import numpy as np
from sklearn.neighbors import NearestNeighbors
from sklearn.preprocessing import StandardScaler
import openai
import json
from tqdm import tqdm


# =============================== Initialization ===============================
api_key = "API KEY"
client = openai.OpenAI(api_key=api_key)
```

```python
# ======================== Configuration and Metadata ========================
USED_FIELDS = [
    "id", "age", "education", "hh_size", "hh_comp", "income",
    "wealth", "ownership", "dwelling_type", "usable_area", "constr_year",
    "elect_cons", "gas_cons", "contact_neigh"
]

FIELD_DESCRIPTIONS = {
    "age": "Age of the household head",
    "education": "Education level of the household head",
    "hh_size": "Total number of people in the household",
    "hh_comp": "Household composition (e.g., adults/children)",
    "income": "Household income",
    "wealth": "Household wealth level",
    "ownership": "Homeownership status",
    "dwelling_type": "Type of dwelling (e.g., apartment or not).",
    "usable_area": "Usable floor area of the home",
    "constr_year": "Construction year of the home",
    "elect_cons": "Monthly electricity consumption",
    "gas_cons": "Monthly gas consumption",
    "contact_neigh": "Level of contact with neighbors"
}
```

```python
EXTERNAL_INFO_BY_YEAR = {
    2021: {
        "Adoption context": (
            "Only around 7% of households in Amsterdam had installed rooftop
           solar or heat pump systems in 2021."
            "This means adoption was still relatively rare."
        ),
        "Financial factors": (
            "Expect to pay roughly €4,000 to €5,000 for 10 solar panels,
           excluding btw."
            "Annual savings could reach €497, and the estimated payback period
           was 4 to 9 years, depending on usage."
        ),
        "Energy prices": (
            "Electricity price is €0.136 per kWh (for households using 2,500-
           5,000 kWh/year)."
        ),
        "Installation access": (
            "Apartments often required coordination with neighbors or housing
           associations, but it is still possible."
        ),
```

```
        "Policy and legal environment": (
            "Some incentives were available, like Salderingsregeling (netting
           scheme)."
            "However, state-protected historic buildings (often older homes)
           required special permits for rooftop installations."
        )
    },
```

```
2022: {
        "Adoption context": (
            "Only around 7% of households in Amsterdam had installed rooftop
           solar or heat pump systems in 2021."
            "This means adoption was still relatively rare."
        ),
        "Financial factors": (
            "Installation costs temporarily increased in 2022 due to supply
           chain issues and inflation. "
            "The average cost per Wattpiek jumped to €1.83, a significant
           increase from €1.20 in 2021."
        ),
        "Energy prices": (
            "Electricity cost €0.105 per kWh (for households using 2,500-5,000
           kWh/year), decreasing a bit from 2021."
        ),
        "Installation access": (
            "Apartments often required coordination with neighbors or housing
           associations, but it is still possible."
        ),
        "Policy and legal environment": (
            "Some incentives were available for homeowner and housing
           associations on solar adoption, like Salderingsregeling (netting
           scheme)."
            "However, state-protected historic buildings (often older homes)
           required special permits for rooftop installations."
        )
    },
```

```
2023: {
        "Adoption context": (
            "Only around 9% of households in Amsterdam had installed rooftop
           solar or heat pump systems in 2023."
        ),
        "Financial factors": (
            "Solar panel prices returned to more affordable levels at €1.24 per
           Wattpiek, similar to 2021 prices. "
            "The BTW (VAT) was removed from solar panel purchases starting in
           2023."
        ),
        "Energy prices": (
            "Electricity cost €0.317 per kWh (for households using 2,500-5,000
           kWh/year), a significant increase from 2022."
        ),
        "Installation access": (
            "Apartments often required coordination with neighbors or housing
           associations, but it is still possible."
        ),
```

```
        "Policy and legal environment": (
            "Some incentives were available for homeowner and housing
          associations on solar adoption, like Salderingsregeling (netting
          scheme)."
            "However, state-protected historic buildings (often older homes)
          required special permits for rooftop installations."
            "The removal of BTW (VAT) on solar panels this year represented a
          financial incentive for homeowners. "
            "The Salderingsregeling (netting scheme) was still in effect,
          allowing homeowners to offset electricity costs."
        )
    },
```

```
2024: {
        "Adoption context": (
            "Only around 9% of households in Amsterdam had installed rooftop
          solar or heat pump systems in 2023."
        ),
        "Financial factors": (
            "The price per Wattpiek dropped to €0.90, the lowest point in the
          historical trend. "
            "With 8 solar panels, the cost is around €3300 and households can
          save approximately €510 per year while the saldering regulation
          applies, "
            "and afterward about €170 per year over the 25-year lifespan of the
          panels."
        ),
        "Energy prices": (
            "Electricity cost €0.243 per kWh (for households using 2,500-5,000
          kWh/year), a decrease from 2023."
        ),
        "Installation access": (
            "Apartments often required coordination with neighbors or housing
          associations, but it is still possible."
        ),
        "Policy and legal environment": (
            "The Salderingsregeling (netting scheme) was still in effect,
          allowing homeowners to offset electricity costs."
            "However, state-protected historic buildings (often older homes)
          required special permits for rooftop installations."
            "On August 20, 2024, the new Amsterdam Sustainable Solar Panel
          Subsidy was launched."
        )
    }
}
```

```
# ============================== Data Processing ==============================

def load_and_preprocess_data(filepath: str, n: int = 50) -> pd.DataFrame:
    df = pd.read_csv(filepath)[USED_FIELDS].copy()
    df["unique_id"] = range(len(df))
    return df

# =========================== Dynamic Field Updates ===========================
def update_household_attributes(df: pd.DataFrame, year: int) -> pd.DataFrame:
    df = df.copy()
    df["income"] = df["income"] * np.random.normal(1.02, 0.08, len(df))
    df["elect_cons"] = df["elect_cons"] * np.random.normal(1.0, 0.05, len(df))
    df["gas_cons"] = df["gas_cons"] * np.random.normal(0.98, 0.03, len(df))
    df["house_age"] = year - df["constr_year"]
    return df
```

```python
# =================== Prompt Construction ===================

def build_profile_paragraph(row: pd.Series, neighbor_adoption_rate: float,
wijk_adoption_rate: float) -> str:
    parts = []
    peer_effect = ""

    if pd.notnull(row["age"]):
        parts.append(f"You are aged {row['age']}")
    if pd.notnull(row["education"]):
        parts.append(f"with a {row['education']} level of education")
    if pd.notnull(row["ownership"]):
        own_text = "own" if row["ownership"] == "owner" else "rent"
        dwelling = row["dwelling_type"] if pd.notnull(row["dwelling_type"])
           else "dwelling"
        parts.append(f"and you {own_text} a {dwelling}")
    if pd.notnull(row["house_age"]):
        parts.append(f"built approximately {int(row['house_age'])} years ago")
    if pd.notnull(row["usable_area"]):
        parts.append(f"with {int(row['usable_area'])} square meters of usable
           area")
    if pd.notnull(row["hh_size"]):
        parts.append(f"You live with a household of {row['hh_size']} people")
    if pd.notnull(row["hh_comp"]):
        parts.append(f"and the composition is '{row['hh_comp']}'")
    if pd.notnull(row["income"]):
        parts.append(f"Your annual household income is €{int(row['income'])}")
    if pd.notnull(row["wealth"]):
        parts.append(f"and your reported wealth is €{int(row['wealth'])}")
    if pd.notnull(row["elect_cons"]):
        parts.append(f"You consume about {int(row['elect_cons'])} kWh of
           electricity per year")
    if pd.notnull(row["gas_cons"]) and row["gas_cons"] > 0:
        parts.append(f"and also use gas ({int(row['gas_cons'])} m³ per year)")
    if pd.notnull(row["contact_neigh"]):
        parts.append(f"You report '{row['contact_neigh']}' levels of contact
           with neighbors")
    if neighbor_adoption_rate != "unknown" and row["contact_neigh"] in ["agree",
           "totally agree"]:
        if neighbor_adoption_rate == 0:
            peer_effect = "None of your close neighbors have installed solar
           panels yet."
        elif neighbor_adoption_rate <= 0.1:
            peer_effect =  "Very few of your neighbors have installed solar
           panels."
        elif neighbor_adoption_rate <= 0.2:
            peer_effect = "A couple of your neighbors have installed solar
           panels."
        elif neighbor_adoption_rate <= 0.3:
            peer_effect = "Some of your neighbors have installed solar panels."
        elif neighbor_adoption_rate <= 0.5:
            peer_effect = "A significant portion of your neighbors have
           installed solar panels."
        elif neighbor_adoption_rate <= 0.7:
            peer_effect = "Many of your neighbors have installed solar panels."
        else:
            peer_effect = "Most of your neighbors have installed solar panels."

        parts.append(peer_effect + " ")
```

```
    if wijk_adoption_rate != "unknown":
        parts.append(
            f"In your local community, around {int(wijk_adoption_rate * 100)}%
           of households have already adopted rooftop solar panels."
        )

    return " ".join(parts) + ". "
```

```
def build_prompt(row: pd.Series, year: int, neighbor_adoption_rate: float,
wijk_adoption_rate: float) -> str:
    row["house_age"] = year - row["constr_year"]
    profile = build_profile_paragraph(row, neighbor_adoption_rate,
           wijk_adoption_rate)
    external_info = EXTERNAL_INFO_BY_YEAR.get(year, EXTERNAL_INFO_BY_YEAR[2021])
    return (
        f"You are a household living in Amsterdam in the year {year}.\n"
        "Based on your household's situation and the policy environment at the
           time, think carefully about whether you have already installed
           rooftop solar panels—or whether you are genuinely and actively
           considering doing so.\n"
        "Consider your financial capacity, energy usage, social context, and
           environmental motivation and so on to see if there are strong
           reasons.\n"
        "Also consider the complexities and frictions involved, such as your
           household size and energy demanding, social context, and the
           potential difficulties in coordinating installation.\n"
        "Even if solar panels seem financially beneficial in theory, many
          households delay or reject adoption due to hesitation, uncertainties,
           or competing priorities.\n"
        "Many families also have concerns about the process being complicated,
           time-consuming, or uncertain. While some may have strong
           environmental motivation or financial incentives, the real-world
           barriers to adoption can often outweigh these motivations.\n\n"
        f"Here is the contextual information as of
           {year}:\n{external_info}\n\n"
        f"Here is your household profile:\n{profile}\n\n"
        "Do not assume a yes or no decision based solely on your dwelling
           type."
        "Please respond in the following JSON format:\n"
        "{\n"
        '  "decision": "yes" or "no",\n'
        '  "reasoning": "A detailed explanation about your decision (2-3
           sentences)..."\n'
        "}"
    )
```

```
def get_system_message(year: int) -> dict:
    return {
        "role": "system",
        "content": (
            f"You are a household in Amsterdam in {year} deciding whether to
           install rooftop solar panels.\n\n"
            f"Around {EXTERNAL_INFO_BY_YEAR[year]['Adoption context']}.\n\n"
            "Adoption often occurs in diverse households—not just those with
           perfect housing conditions.\n\n"
            "Consider economic, behavioral, and situational factors, such as
           income, energy demands, trust in technology, household composition,
           roof access, and social norms.\n\n"
```

```
            "Your decision should reflect the real-world context, where most
           households do not act purely on financial logic—real-world decisions
           often involve hesitation, competing priorities, and behavioral
           friction.\n\n"
            "Households may also have different environmental attitude,
           political stance and investment propensity.\n\n"
            "Even households with environmental concerns or financial means may
           feel unsure. Uncertainties and competing priorities often make it
           easy to postpone such decisions.\n"
            "Most households do not act purely based on economic logic. It is
           common to hesitate or postpone installation due to doubts, inertia,
           lack of time, or concern about complexity.\n"
            "**Do not assume a yes or no decision based solely on dwelling
           type.** Some people living in 'non-apartment' also face complexity,
           while many apartments have successfully installed panels when owners
           are proactive or feel connected to their community.\n\n"
            "Weigh all relevant factors fairly and realistically.\n"
            "Respond only in strict JSON format."
        )
    }
```

```
# ============================== LLM Interaction ==============================

def query_llm(prompt: str, year: int) -> dict:
    try:
        messages = [get_system_message(year), {"role": "user", "content":
prompt}]
        response = client.chat.completions.create(
            model="gpt-4o-mini",
            messages=messages,
            temperature=0,
            response_format={"type": "json_object"},
            top_p=1.0,
            frequency_penalty=0,
            presence_penalty=0,
        )
        content = response.choices[0].message.content.strip()

        if content.startswith("```"):
            content_parts = content.split("```")
            if len(content_parts) > 1:
                content = content_parts[1].strip()
                if content.startswith("json"):
                    content = content[len("json"):].strip()

        try:
            return json.loads(content)
        except json.JSONDecodeError as json_err:
            print(f"JSON parsing error: {json_err}")
            print(f"Full content received:\n{content}")
            return {"decision": None, "reasoning": f"JSON parsing error:
{str(json_err)}"}
    except Exception as e:
        print("LLM Error:", e)
        return {"decision": None, "reasoning": str(e)}
```

```python
# ==================== Neighbor Structures ====================

def build_fixed_neighbors(df, k=10):

    features_df = df.copy()

    if 'age' in features_df.columns:
        def process_age(age):
            if isinstance(age, str) and '-' in age:
                try:
                    lower, upper = map(int, age.split('-'))
                    return (lower + upper) / 2
                except (ValueError, TypeError):
                    return np.nan
            elif pd.isna(age):
                return np.nan
            else:
                try:
                    return float(age)
                except (ValueError, TypeError):
                    return np.nan
        features_df['age'] = features_df['age'].apply(process_age)

    if 'income' in features_df.columns:
        def process_income(income):
            if pd.isna(income):
                return np.nan
            try:
                return float(income)
            except (ValueError, TypeError):
                return np.nan
        features_df['income'] = features_df['income'].apply(process_income)

    if 'usable_area' in features_df.columns:
        def process_area(area):
            if pd.isna(area):
                return np.nan
            try:
                return float(area)
            except (ValueError, TypeError):
                return np.nan
        features_df['usable_area'] =
           features_df['usable_area'].apply(process_area)

    features = features_df[['income', 'age', 'usable_area']].fillna(0)
    scaler = StandardScaler()
    scaled_features = scaler.fit_transform(features)
    nbrs = NearestNeighbors(n_neighbors=min(k+1, len(df)),
           algorithm='auto').fit(scaled_features)
    distances, indices = nbrs.kneighbors(scaled_features)
    fixed_neighbors_dict = {}
    for i, idx_list in enumerate(indices):
        neighbors_indices = [j for j in idx_list if j != i][:k]
        fixed_neighbors_dict[df.iloc[i]['unique_id']] = [df.iloc[j]['unique_id’]
           for j in neighbors_indices]
    return fixed_neighbors_dict
```

```python
def build_dynamic_neighbors(df, year=None, k=10):

    if year is not None:
        np.random.seed(year)
    dynamic_neighbors_dict = {}
    for idx, row in df.iterrows():
        possible_neighbors = df[df['unique_id'] !=
           row['unique_id']]['unique_id'].values
        actual_k = min(k, len(possible_neighbors))
        neighbors = np.random.choice(possible_neighbors, size=actual_k,
           replace=False)
        dynamic_neighbors_dict[row['unique_id']] = list(neighbors)

    if year is not None:
        np.random.seed(None)

    return dynamic_neighbors_dict

def build_mixed_neighbors(df, year, fixed_neighbors_dict, k=10,
           dynamic_ratio=0.4):

    dynamic_neighbors_dict = build_dynamic_neighbors(df, year, k)
    mixed_neighbors_dict = {}

    for household_id in df['unique_id'].values:
        fixed_neighbors = fixed_neighbors_dict.get(household_id, [])
        dynamic_neighbors = dynamic_neighbors_dict.get(household_id, [])

        fixed_count = int((1 - dynamic_ratio) * k)
        dynamic_count = k - fixed_count
        fixed_count = min(fixed_count, len(fixed_neighbors))
        dynamic_count = min(dynamic_count, len(dynamic_neighbors))
        mixed_neighbors = list(fixed_neighbors[:fixed_count])
        dynamic_to_add = [n for n in dynamic_neighbors[:dynamic_count*2] if n
           not in mixed_neighbors]
        mixed_neighbors.extend(dynamic_to_add[:dynamic_count])
        mixed_neighbors_dict[household_id] = mixed_neighbors

    return mixed_neighbors_dict
```

```python
# ============================ Simulation Logic ============================

def simulate_years(df, num_years=4, k=10, output_file="results_combined.csv"):

    fixed_neighbors_dict = build_fixed_neighbors(df, k)
    yearly_results = {}
    all_years_data = df[["unique_id", "id"]].copy()

    for year in range(2021, 2021 + num_years):
        print(f"Simulating year {year}...")

        mixed_neighbors_dict = build_mixed_neighbors(df, year,
           fixed_neighbors_dict, k)
        df = update_household_attributes(df, year)

        if year - 1 in yearly_results:
            previous_year_df = yearly_results[year - 1]
            wijk_adoption_rate = previous_year_df[f"{year -
           1}_decision"].value_counts(normalize=True).get("yes", 0)
        else:
            wijk_adoption_rate = "unknown"

        neighbor_adoption = {}
```

```python
        for household_id in df["unique_id"]:
            neighbors = mixed_neighbors_dict.get(household_id, [])
            if year - 1 not in yearly_results:
                neighbor_adoption[household_id] = "unknown"
            else:
                adopted_neighbors = sum(
                    1 for neighbor in neighbors
                    if neighbor in previous_year_df["unique_id"].values and
                    previous_year_df.loc[previous_year_df["unique_id"] ==
                      neighbor, f"{year - 1}_decision"].values[0] == "yes"
                )
                neighbor_adoption[household_id] = adopted_neighbors /
                      max(len(neighbors), 1)

        year_decisions = []
        year_reasons = []

        for idx, row in tqdm(df.iterrows(), total=len(df), desc=f"Year {year}
           progress", leave=False):
            if year - 1 in yearly_results:
                prev_decision =
           previous_year_df.loc[previous_year_df["unique_id"] ==
           row["unique_id"], f"{year - 1}_decision"]
                if not prev_decision.empty and prev_decision.values[0] == "yes":
                    year_decisions.append("yes")
                    year_reasons.append("Already adopted in a previous year.")
                    continue

            neighbor_rate = neighbor_adoption.get(row["unique_id"], 0) if
           row["contact_neigh"] in ["agree", "totally agree"] else 0
            prompt = build_prompt(row, year, neighbor_rate, wijk_adoption_rate)
            result = query_llm(prompt, year)

            year_decisions.append(result["decision"])
            year_reasons.append(result["reasoning"])

        df[f"{year}_decision"] = year_decisions
        df[f"{year}_reasoning"] = year_reasons
        yearly_results[year] = df[["unique_id", f"{year}_decision",
           f"{year}_reasoning"]].copy()

        all_years_data = all_years_data.merge(yearly_results[year],
           on="unique_id", how="left")

        print(f"Year {year}: Simulation completed.")

    all_years_data.to_csv(output_file, index=False)
    print(f"All years' results saved in '{output_file}'.")

    return yearly_results
```

```python
# ================================ Main Logic ================================

if __name__ == "__main__":
    input_file = "synthetic_population_zone_5_owner.csv"
    output_file = "250524_results_zone5.csv"
    df = load_and_preprocess_data(input_file)
    yearly_results = simulate_years(df, num_years=4, k=10,
           output_file=output_file)
    print(f"Done. Results saved in '{output_file}'.")
```

Appendix D Additional Simulation Results Analysis

Table D-1 Simulated adoption rate and growth rate per household composition type (%)

Household composition	Adoption rate				Growth rate		
	2021	2022	2023	2024	2021 -> 2022	2022 -> 2023	2023 -> 2024
one-parent	5.88	5.88	7.84	7.84	0	33.33	0
couple	7.47	8.12	11.24	13.84	8.7	38.42	23.13
single-person	3.95	4.22	6.06	7.97	6.84	43.6	31.52
couple+children	19.56	20.03	22.56	29.34	2.4	12.63	30.05
other	0	0	4.35	8.7	-	-	100

Table D-2 Simulated adoption rate and growth rate per household size group (%)

Household size	Adoption rate				Growth rate		
	2021	2022	2023	2024	2021 -> 2022	2022 -> 2023	2023 -> 2024
1 person	3.95	4.22	6.06	7.97	6.84	43.6	31.52
2 people	7.35	7.97	11.06	13.53	8.44	38.77	22.33
3 and more	17.67	18.08	20.55	26.58	2.32	13.66	29.34

Table D-3 Simulated adoption rate and growth rate per livable area category (%)

Housing livable area (sqm)	Adoption rate				Growth rate		
	2021	2022	2023	2024	2021 -> 2022	2022 -> 2023	2023 -> 2024
0-40	0	0	3.05	8.54	-	-	180
40-60	0.48	0.48	2.73	3.33	0	468.75	21.98
60-80	2.38	2.38	3.42	4.97	0	43.7	45.32
80-100	7.31	7.86	9.66	12.55	7.52	22.9	29.92
100+	19.47	20.58	24.77	30.15	5.7	20.36	21.72

Factors	Motives		Barriers	
	Apartment	Non-apartment	Apartment	Non-apartment
age	0.47	0.67	4.53	5.62
cost	1.95	8.21	31.73	13.95
education	20.18	7.31	1.98	2.25
electricity prices	1.01	5.29	0	0.11
energy consumption	16.99	27.22	20.35	9.9
environmental motivation	61.01	68.95	1.18	0.79
economic benefits	24.24	35.55	15.48	12.71
financial capacity	96.44	97.53	4.7	3.71
house age	3.76	0	21.05	2.47
household composition	1.11	3.37	7.96	9.22
dwelling type	1.04	33.52	85.49	24.07
installation process	9.27	20.81	99.29	93.48
livable area	0.57	2.47	4.06	6.19
neighborhood effects	7.56	28.68	49.73	45.78
policy incentive	3.22	2.02	0.77	0.34
policy regulation	0.44	0.34	20.62	10.12
technical attitude	0.17	0	0.03	0
others	0.54	0.22	18.07	30.03

Figure D-1 Relative frequency of motives and barriers per dwelling type (%)

Factors	Motives			Barriers		
	High	Middle	Low	High	Middle	Low
age	0.25	1.14	1.64	3.1	8.76	11.48
cost	3.53	3.05	2.87	26.81	31.22	25.82
education	22.57	0	10.66	0	0	32.38
electricity prices	2.68	0.13	0	0.04	0	0
energy consumption	17.39	27.66	15.16	16.58	24.62	12.3
environmental motivation	64.13	61.93	50.82	0.78	2.41	0.41
economic benefits	24.9	33.25	28.69	13.12	22.46	10.25
financial capacity	98.13	93.27	90.98	2.96	7.61	11.89
house age	3.67	1.02	0	20.32	7.74	4.92
household composition	1.62	1.65	1.64	7.8	9.52	9.43
dwelling type	10.05	3.55	6.56	72.77	65.86	72.95
installation process	12.7	6.98	18.85	97.92	97.72	99.18
livable area	1.31	0.25	0	4.8	3.81	4.1
neighborhood effects	12.28	12.69	13.11	47.44	51.78	55.33
policy incentive	3.32	1.9	2.05	0.88	0.13	0
policy regulation	0.46	0.38	0	20.92	11.8	7.38
technical attitude	0.07	0.38	0	0.04	0	0
others	0.42	0.63	0.41	19.82	23.48	23.77

Figure D-2 Relative frequency of motives and barriers per education level group (%)

Factors	Motives				
	Single	Couple	one-parent	couple+children	other
age	0.59	0.58	0	0	8.7
cost	2.04	3.38	5.23	5.52	21.74
education	22.66	17.35	15.03	4.57	13.04
electricity prices	0.26	2.86	1.31	4.26	0
energy consumption	11.46	22.48	15.69	31.23	26.09
environmental motivation	59.75	64	62.75	68.14	43.48
economic benefits	22.13	27.03	26.8	37.54	30.43
financial capacity	93.87	99.42	90.85	98.11	100
house age	3.23	2.08	1.96	4.26	4.35
household composition	2.5	0.06	0.65	3.63	0
dwelling type	5.4	8.51	11.11	15.3	8.7
installation process	10.08	10.27	9.8	20.98	0
livable area	0.33	0.97	1.96	2.52	8.7
neighborhood effects	9.55	10.46	13.73	23.82	8.7
policy incentive	1.52	4.35	1.96	3.31	0
policy regulation	0.46	0.26	0	0.79	0
technical attitude	0.26	0	0	0.16	0
others	0.72	0.13	0	0.79	0

Factors	Barriers				
	Single	Couple	one-parent	couple+children	other
age	8.83	3.25	0	0	4.35
cost	34.32	21.51	39.87	24.29	8.7
education	1.78	2.73	2.61	0.63	8.7
electricity prices	0	0.06	0	0	0
energy consumption	32.94	9.42	15.69	3.94	0
environmental motivation	0.66	1.43	1.96	0.95	4.35
economic benefits	25.49	8.25	15.03	5.52	8.7
financial capacity	8.1	1.17	9.15	2.84	0
house age	16.8	19.3	7.19	13.25	8.7
household composition	19.37	0.06	14.38	0.32	0
dwelling type	66.4	77.84	66.67	68.61	73.91
installation process	98.81	98.77	100	93.38	100
livable area	3.16	7.28	1.96	1.74	8.7
neighborhood effects	56.19	47.5	51.63	32.81	73.91
policy incentive	1.45	0.19	0.65	0	0
policy regulation	15.94	21.57	15.69	15.77	26.09
technical attitude		0.06	0	0	0
others	16.53	22.61	26.14	25.55	17.39

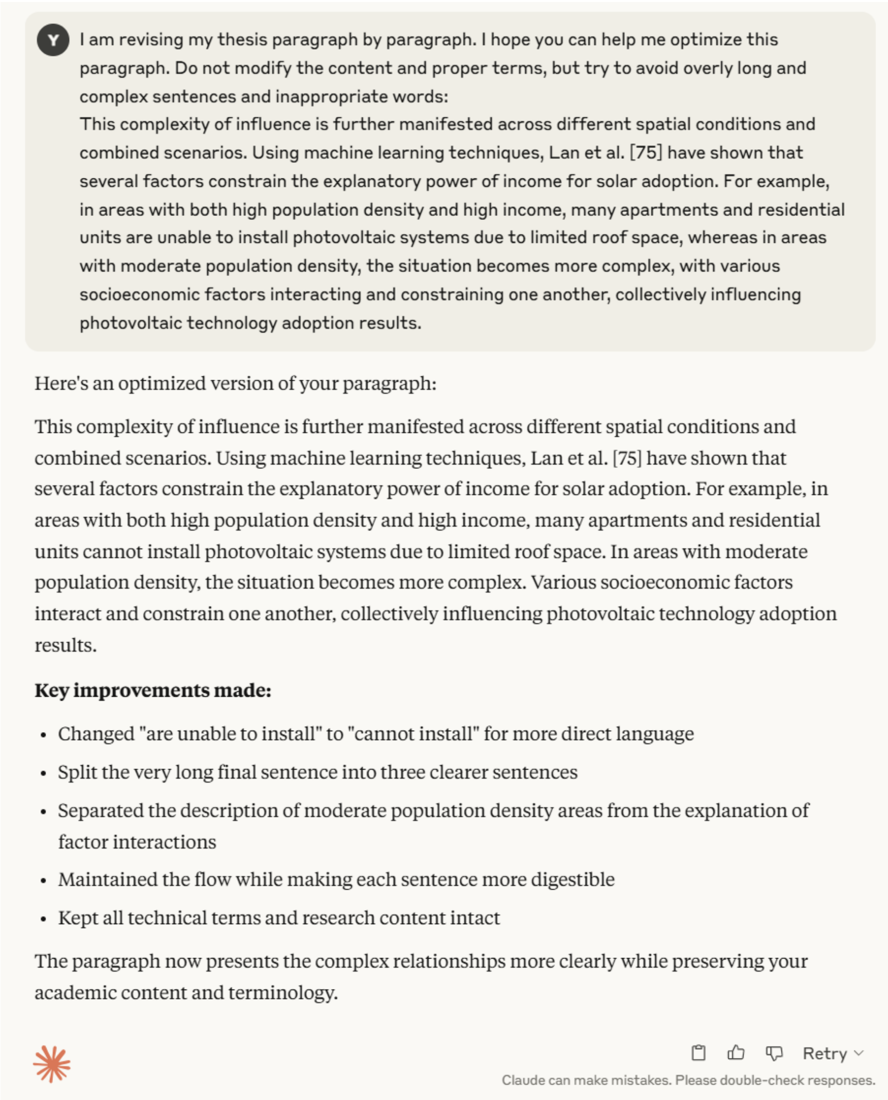
Figure D-3 Relative frequency of motives and barriers per household composition category (%)

Factors	Motives					Barriers				
	0-40	40-60	60-80	80-100	100+	0-40	40-60	60-80	80-100	100+
age	1.22	0.12	0.31	0.97	0.6	0.61	2.26	7.05	5.66	4.78
cost	0.61	1.54	2.07	2.9	6.49	37.8	38.24	35.44	27.31	12.38
education	40.85	27.91	20.41	12.83	6.32	5.49	0.95	3.01	3.03	0.94
electricity prices	0	0.24	0.1	2.07	5.04	0	0	0	0	0.09
energy consumption	3.66	12.71	17.82	22.21	25.79	42.68	27.32	22.07	14.34	6.58
environmental motivation	51.22	57.01	61.76	65.66	67.81	0.61	1.54	1.04	0.97	0.94
economic benefits	28.66	20.31	25.18	29.79	30.83	32.93	22.21	17.93	11.59	6.49
financial capacity	80.49	96.44	98.13	97.24	97.61	17.68	6.06	2.8	3.31	3.59
house age	0	4.99	1.45	2.9	2.99	29.88	22.33	16.89	11.72	14.01
household composition	0.61	1.9	1.66	1.24	1.79	18.29	9.62	8.81	7.17	6.06
dwelling type	0.61	1.31	3.32	7.31	19.81	85.37	84.44	76.99	72.55	54.65
installation process	9.15	11.4	7.46	12.55	15.97	100	98.93	99.69	98.07	95.47
livable area	0.61	0.24	0.52	0.69	2.22	3.66	4.51	5.18	3.03	5.12
neighborhood effects	13.41	4.28	6.11	12.41	23.31	56.71	56.65	52.64	44.41	41.67
policy incentive	1.83	2.85	3.73	2.62	2.73	1.22	0.95	0.93	0.83	0.09
policy regulation	0	0.48	0.62	0	0.51	20.12	27.67	17.82	15.59	13.07
technical attitude	0.61	0.12	0.1	0.28	0	0	0.12	0	0	0
others	0	0.95	0.41	0.69	0.09	12.8	14.73	22.69	23.72	22.97

Figure D-4 Relative frequency of motives and barriers per livable area category (%)

Appendix E Usage of Generative AI

As mentioned in Chapter 3, apart from the LLM-based agent at the core of this research which inevitably requires OpenAI's large language model API, the use of generative AI in this study is limited to text polishing (non-content) and coding assistance for logic implementation, and debugging. **Claude Sonnet 4** is primarily used in this case. The following are respective examples:



Y I am revising my thesis paragraph by paragraph. I hope you can help me optimize this paragraph. Do not modify the content and proper terms, but try to avoid overly long and complex sentences and inappropriate words:
This complexity of influence is further manifested across different spatial conditions and combined scenarios. Using machine learning techniques, Lan et al. [75] have shown that several factors constrain the explanatory power of income for solar adoption. For example, in areas with both high population density and high income, many apartments and residential units are unable to install photovoltaic systems due to limited roof space, whereas in areas with moderate population density, the situation becomes more complex, with various socioeconomic factors interacting and constraining one another, collectively influencing photovoltaic technology adoption results.

Here's an optimized version of your paragraph:

This complexity of influence is further manifested across different spatial conditions and combined scenarios. Using machine learning techniques, Lan et al. [75] have shown that several factors constrain the explanatory power of income for solar adoption. For example, in areas with both high population density and high income, many apartments and residential units cannot install photovoltaic systems due to limited roof space. In areas with moderate population density, the situation becomes more complex. Various socioeconomic factors interact and constrain one another, collectively influencing photovoltaic technology adoption results.

Key improvements made:

- Changed "are unable to install" to "cannot install" for more direct language
- Split the very long final sentence into three clearer sentences
- Separated the description of moderate population density areas from the explanation of factor interactions
- Maintained the flow while making each sentence more digestible
- Kept all technical terms and research content intact

The paragraph now presents the complex relationships more clearly while preserving your academic content and terminology.

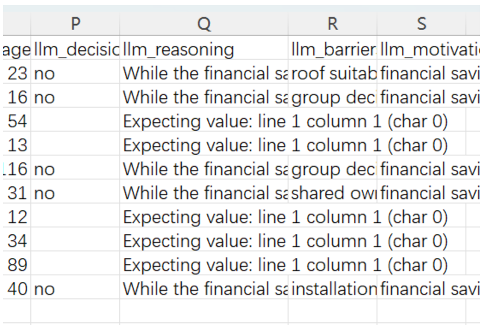
Retry

Claude can make mistakes. Please double-check responses.

Figure E-1 Example of AI used in language improvement

As a non-native speaker, my English writing skills is limited, thus I utilize AI to assist optimize my wording while avoiding improper word choices. The image above is a true example (the paragraph is from Section 4.3). My document featured excessively long sentences, therefore I followed AI advice and cut down the huge statement beginning with "For example..." into several shorter ones. Furthermore, while the AI did not say it, I saw a comparable and developing link between the two situations, so I added "Furthermore" myself. Also, I felt that "cannot" was too harsh in this example, therefore I did not modify the word as AI suggested. The revised segment is as follows:

"This complexity of influence is further demonstrated across different spatial conditions and combined scenarios. Using machine learning techniques, Lan et al. [75] have shown that several factors limit the explanatory power of income for solar adoption. For example, in areas with both high population density and high income, many apartments and residential units are unable to install PV systems due to limited roof space. Furthermore, in areas with moderate population density, the situation becomes more complex. Various socioeconomic factors interact and constrain one another, collectively influencing PV technology adoption outcomes."



	P	Q	R	S
age	llm_decisic	llm_reasoning	llm_barrier	llm_motivati
23	no	While the financial sa	roof suitab	financial savi
16	no	While the financial sa	group dec	financial savi
54		Expecting value: line 1 column 1 (char 0)		
13		Expecting value: line 1 column 1 (char 0)		
.16	no	While the financial sa	group dec	financial savi
31	no	While the financial sa	shared owi	financial savi
12		Expecting value: line 1 column 1 (char 0)		
34		Expecting value: line 1 column 1 (char 0)		
89		Expecting value: line 1 column 1 (char 0)		
40	no	While the financial sa	installation	financial savi

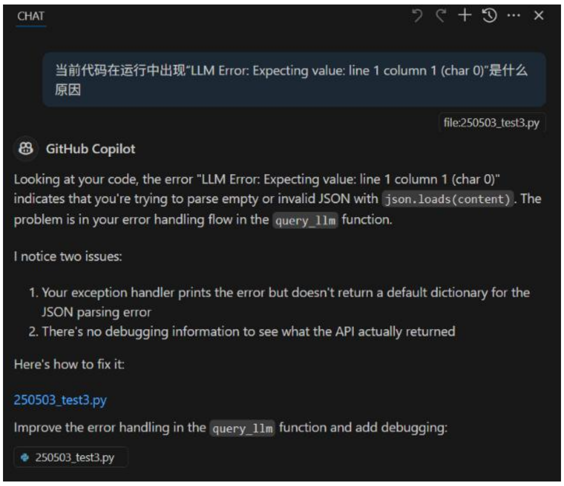
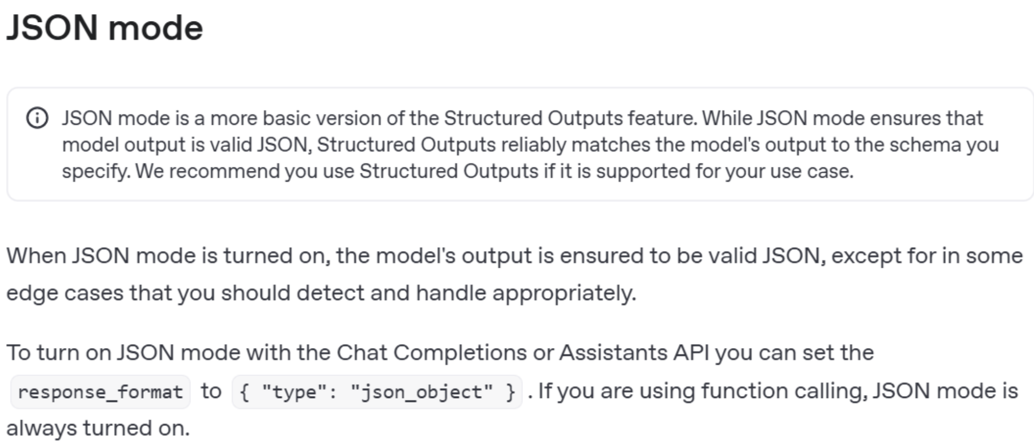


Figure E-2 Example of AI used in coding

The usage of AI in the coding process is mainly via GitHub Copilot in VSCode based on the Claude Sonnet 4 model. There was a situation where I encountered output errors in the early stages of model development. I couldn't identify where the code was wrong, so I used Copilot to help me check the cause. It suggested that the issue might be due to the output format not being strict JSON, and provided some modification suggestions. However, its modification didn't work effectively. Therefore, I went to check OpenAI's official documentation by myself and found a simple method to make the output format JSON, as shown in Figure E-3.



JSON mode

JSON mode is a more basic version of the Structured Outputs feature. While JSON mode ensures that model output is valid JSON, Structured Outputs reliably matches the model's output to the schema you specify. We recommend you use Structured Outputs if it is supported for your use case.

When JSON mode is turned on, the model's output is ensured to be valid JSON, except for in some edge cases that you should detect and handle appropriately.

To turn on JSON mode with the Chat Completions or Assistants API you can set the `response_format` to `{ "type": "json_object" }`. If you are using function calling, JSON mode is always turned on.

Figure E-3 Instructions on OpenAI document (source: https://platform.openai.com/docs/guides/structured-outputs?api-mode=chat)

Overall, I believe generative AI has provided me with significant help in improving my language and has also enhanced my programming efficiency. However, it is not always correct, and during usage, there have been instances where it altered specialized terminology in my thesis or split sentences in ways that made the logic incoherent. Therefore, it needs to be approached with caution. This process itself is a good exercise