TRANSITION DYNAMICS IN RESIDENTIAL HEATING SYSTEMS: AN AGENT-BASED MODELING APPROACH

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Abstract

The urgent global need to reduce carbon emissions has intensified the focus on transitioning to sustainable energy solutions. Residential heating is a significant contributor to greenhouse gas emissions. As such, understanding the factors influencing this shift towards more sustainable heating solutions, such as gas-free heat pumps, is critical. This study employs an agent-based model (ABM) to examine the dynamics of adopting sustainable residential heating systems, with a special emphasis on the transition to a gas-free community. The model integrates individual household preferences, financial capabilities, environmental concerns, and social influences to understand the collective transition. The paper illustrated the methodology through a numerical simulation.

Keywords: Agent-based modeling, residential heating, energy efficiency.

Introduction

The imperative to curtail global carbon emissions has intensified the efforts to transition towards sustainable energy solutions. Among the significant contributors to greenhouse gas emissions, residential heating stands out, necessitating a profound shift towards environmentally friendly alternatives. For example, the Netherlands is ranked in the top 5 in the EU for per capita greenhouse gas emissions, largely due to residential heating, which contributes about 10% of national emissions (PBL, 2020). The predominant use of natural gas for home heating is a key factor (de Wildt et al., 2021).

The transition to a sustainable heating system faces challenges in collective decision-making. These challenges stem from varying priorities and constraints among homeowners, including economic considerations and personal preferences. The complexity increases with the need to align these diverse viewpoints for the community-wide adoption of sustainable heating solutions.

Traditional equation-based models (EBMs) have been widely used to predict the diffusion of energy technologies, however, their ability to capture the nuances of individual behavior and complex system dynamics is limited (Moglia et al., 2017). EBMs typically excel in forecasting aggregate behavior but often fall short in depicting interactions at the micro-level, which are crucial for understanding the intricacies of decision-making for energy-related investment.

Agent-based models (ABM) emerge as a robust alternative, addressing these complexities by facilitating a detailed and realistic representation of individual agents and their interactions within a socio-technical framework. ABMs offer an in-depth view of system dynamics, integrating agent heterogeneity, social behavior, and geospatial elements. They allow for an exploration of non-linear relationships and the impact of individual decisions, providing a comprehensive understanding of diffusion patterns at both individual and collective scales (Hansen et al., 2019; Hesselink & Chappin, 2019).

ABM's flexibility in simulating various scenarios helps in understanding the potential outcomes of different heating system implementations, considering the unique dynamics of the homeowner decision-making (Rahmandad & Sterman, 2008). This intricate decision-making process encompasses the delicate balance homeowners trike between economic incentives, environmental concerns, social pressures, and how individual preferences and constraints shape their decisions towards heating system investments. By simulating these varied decision-making processes, ABMs can capture the complexity and heterogeneity inherent in homeowner behaviors, providing insights that are often overlooked in traditional modeling approaches.

The motivation for this research stems from the urgent need to support the transition to sustainable heating systems in a way that is both environmentally beneficial and socially acceptable. By developing a model that simulates household decision-making processes and examines the influence of factors such as economic incentives and social influence, this study aims to contribute insights into the diffusion of sustainable heating technologies. Ultimately, the goal is to inform and guide effective planning strategies that can accelerate the adoption of sustainable heating solutions, aligning homeowner decisions with broader environmental objectives.

This paper begins with an overview of background and significance, then introduces the model in detail, including design, agent attributes, and decision-making processes. The subsequent section presents the simulation setup, execution, and findings, illuminating the model's insights into sustainable heating adoption. The next discussion section links these results to wider real-world implications, leading to a conclusion section that summarizes key findings and suggests avenues for further research.

Methodology

An agent-based model was constructed using the Mesa framework (Kazil et al., 2020) to examine the dynamics of adopting sustainable residential heating systems. This model is strategically designed to address the limitations commonly found in traditional equation-based models, namely their inadequate representation of individual behaviors and the static nature of social interactions

(Moglia et al., 2017; Natarajan et al., 2011; Rounsevell et al., 2012). This model brings agent heterogeneity into consideration, also adds spatial dynamics which traditional ones are hard to simulate. By integrating a detailed representation of household behavior within a socio-technical system, the approach aids in finding real-world emerging patterns to proposed heating solutions, thus enhancing the effectiveness of planning and implementation strategies.

Model Structure

Agents in the model are autonomous entities representing individual households. Each agent is characterized based on statistical distributions that reflect socio-demographic profiles and social clustering data, consistent with real-world demographics. The agents are programmed to evaluate and possibly adopt energy technologies at each simulation step, contingent upon their unique states and decision-making rules. These rules are algorithmic representations of how agents convert their internal states into actions.

The internal state of an agent encompasses a range of parameters such as income, savings, environmental concern, energy efficiency concern, and more. The state evolves as the agent interacts within its social network and makes decisions based on a utility function that integrates the Theory of Planned Behavior with the Net Present Value (NPV) of potential investments.

The Theory of Planned Behavior (TPB) (Ajzen, 1991, 2002; Schiera et al., 2019), which is a widely used human behavior theory, explains human behavior through three attributes: Attitude Toward the Behavior, Subjective Norm, and Perceived Behavioral Control. The intensity of the behavior and the individual's commitment to action are influenced by the weighted contributions of these attributes.

The utility function, which calculates the behavioral intention in this model, is weighted by the agent's attitudes toward each technology, perceived social pressure, and perceived behavioral control, alongside environmental and energy efficiency factors.

The environment provides a virtual space for agents to interact and includes resources such as energy technologies and market prices.

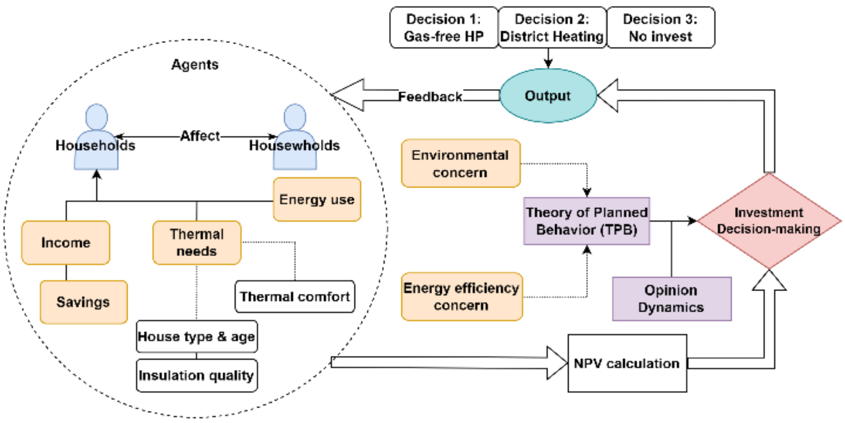

Figure 1. Conceptual ABM framework.

Figure 1 illustrates the conceptual ABM framework, where each household agent has some attributes: income, savings, energy use, and thermal needs. The thermal needs are influenced by house type, house age, the number and vulnerability of family members, and house insulation quality. The agents are faced with three primary decisions: to invest in a gas-free heat pump, district heating with gas, or to refrain from investing. These decisions are shaped by the agents' different concerns and the financial assessment. Feedback mechanisms are in place to reflect the evolving preferences and societal norms as agents interact and make investment decisions.

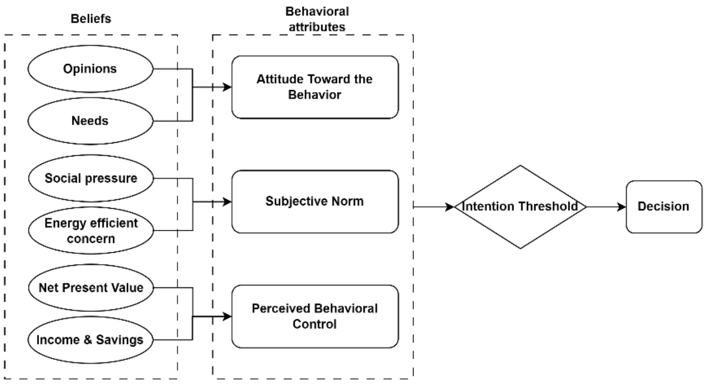

Figure 2. The behavioral sub model of decision-making process in the ABM model.

Figure 2 outlines the decision-making framework based on the Theory of Planned Behavior, which sets the decision-making rules for agents. The process begins with a range of input factors that influence an agent’s beliefs, attitudes, and perceptions. 'Subjective Norm' is influenced by social aspects, such as the choices made by neighbors, reflecting the social pressure component. 'Perceived Behavioral Control' encompasses the agent’s perception of the ease or difficulty of performing the behavior, which in this case could include financial constraints and thermal needs. The TPB weights are adopted from a survey conducted in the Netherlands (Niamir et al., 2018). Changing the weights would lead to different agents’ behavior in the decision-making part.

These three constructs converge to form a 'Behavioral Intention' which is a critical determinant of whether the decision to invest will be made. If the value of this intention is higher than the intention threshold, the agent would decide to invest. Since there are two possible invest options in the model, only the one with higher value would be considered as household’s decision. The decision is the final outcome of this process, indicating whether the agent will act on the intention to invest.

Decision-Making Process

To detail the model setting, the parameters adopted in the model is detailed in Tables 1 and 2. Table 1describes the difference between these investment options. Table 2 shows the parameters in the model, income and energy usage values are obtained from open-source datasets about the Netherlands, where N means normal distribution. These parameters collectively influence the final decision-making process.

Table 1. Comparison of Heating System Investment Options.

Attributes	**Heat Pump***	**District Heating**	**No invest/ keep original**
Investment Cost	Very High	Medium	None
Energy Cost	Low to Medium	Medium	High
CO2 emission	Near Zero	Medium to High	Very High
Energy efficiency	High	Medium	Low
Lifespan	Around 15 years	Over 30 years	Around 15-25 years

***** Note: The Heat Pump category only includes gas-free options such as Air-source, Geothermal, or Solar Heat Pumps.

Table 2. Descriptions of Parameters/ Agent profiles in the model (euros). (Grimm et al., 2010; Müller et al., 2013)

Parameter	**Value**	**Influence on Decision**
	Household Characteristics	
Income (euros/m)	N(47120, 25210), Min: 3250 (*StatLine*, n.d.)	Determines investment capability
Environment Concern	N(0.35,0.1) (OECD, 2023)	Increases intention for environmentally friendly choices
Thermal Need	Calculate based on occupants and house situation	Affects the choices of heating systems
Occupants Number & Vulnerability	Uniform Integers [1,5]; See in Figure 3.	Influences thermal need
Insulation Quality	N(5,2)	Affects thermal need and perceived system efficiency
Energy Usage	N(2780, 1548), Positively clipped (Netherlands, 2023)	Affects energy costs and NPV calculations
	Investment Options	
Invest Costs	HP: 12000* DH: 4500	Upfront cost affects the decision
Net Present Value (NPV)	Calculated based on costs	Affects the long-term perceived benefits
Discount Rates	Calculated from interest rate	Used in NPV calculation
Energy Cost	Varies based on energy source	Affects running costs
Lifespan	HP: 15 years; DH: 30 years	Affects the discount rate and NPV calculation
CO2 Emission Factors	Varies by system type (Blum et al., 2010)	Impacts the environmental utility for each decisions

*Note: Initial costs, would change based on year used and energy cost.

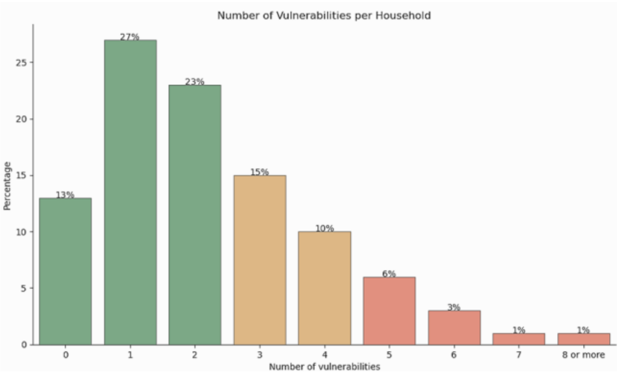

Figure 3. Number of vulnerabilities per household in the Netherlands. (*Many Dutch Are Doing Well, but for Some, Vulnerabilities Are Accumulating*, n.d.)

The thermal need is calculated by multiplying the number of occupants, the presence of vulnerable individuals, insulation quality with adjustment factors for house age, and heating system energy efficiency.

$$NPV = \sum_{0}^{t} (B_t - C_t)/(1+i)^t - C_0$$

The formula is for the calculation of Net Present Value. It calculates the present value of a series of benefits B_t minus costs C_t over a period t, discounted by the average annual bank interest rate i. C_0 is the initial cost.

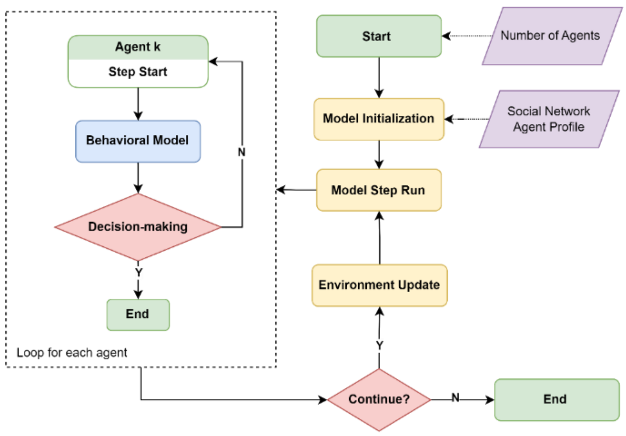

Figure 4. Decision-making process of the ABM framework.

The decision-making process is illustrated in Figure 4. The model is initialized with 1,000 households, each assigned a set of attributes, whose values are randomly generated based on the distributions, according to Table 2. The simulation runs over 15 steps in a loop, with each step representing a year. In each loop of the simulation, which represents one-time decision-making process, agents update their decisions based on various factors, including the recent choices made by their neighbors. This dynamic interaction introduces a layer of social influence, whereby the decisions made by an agent's neighbors in the current loop can affect the agent's own decision-making process in the same loop. Along with these social affects, households annually reassess and update their intentions and financial estimations, leading to potential changes in decision-making. Energy costs are also subject to an annual inflation rate, influencing the NPV calculations and thereby affecting investment decisions over time.

At each simulation step, results are collected on the number of households installing each heating system type and their corresponding investments. After running 15 steps, the agent decides on a heating system, which is the final of the simulation's set duration. This reflects the real-world scenario where investments in heating systems are long-term and rarely reversed. Post-simulation, the percentage of households opting for each heating system is calculated and analyzed to understand the prevailing trends and the impact of the considered factors.

Results

A numerical simulation has been performed in this study. The simulation demonstrates an increasing preference for gas-free heat pumps, indicating a collective inclination toward sustainable options. Heat pumps show higher adoption rates compared to gas district heating, as evidenced by the histogram distribution of final choices. The simulation results of 100 runs are presented below:

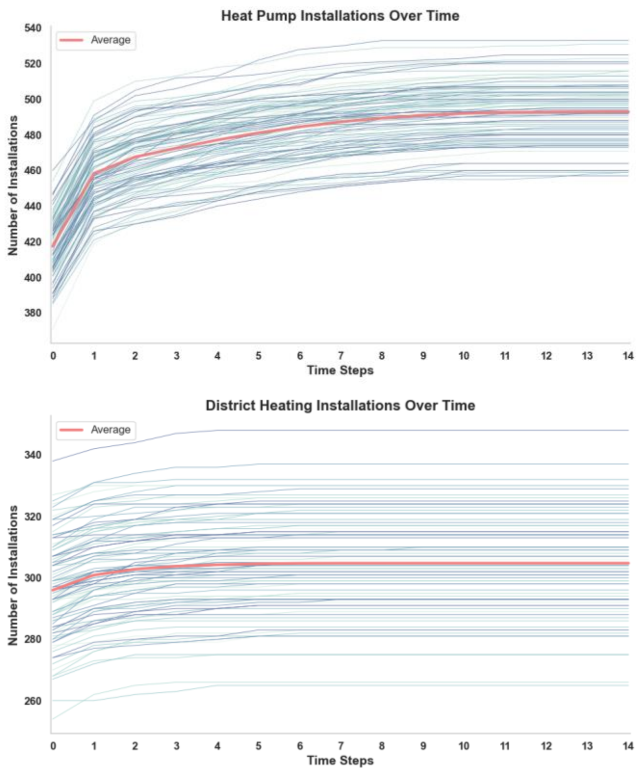

Figure 5. Installation numbers of each investment option across multiple simulation runs.

An upward trend for gas-free heat pump is evident, with a converging average suggesting a growing preference.

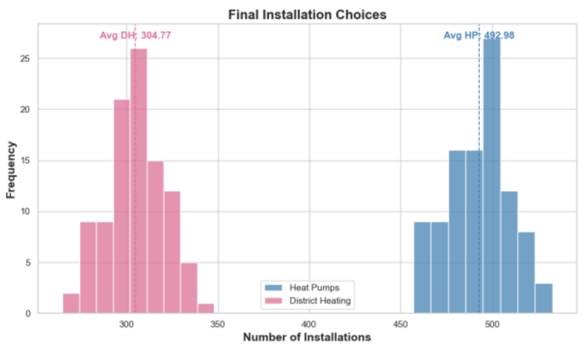

Figure 6. Final Installation Choices Histogram of the distribution of final choices.

Indicating a higher adoption rate for heat pumps over gas heating.

Table 3. Overall mean percentage of households' decisions.

Overall Mean Percentage in the Households		
Gas-free Heat Pump	District Heating	No Invest
49.30%	30.48%	20.23%

Discussion

The agent-based model's simulation process could reveal discernible patterns in household heating system decisions. The multi-objective nature of the model encapsulates the trade-offs between cost, efficiency, lifespan, and environmental impact.

There is a robust inclination towards gas-free heat pumps, despite their higher costs and reduced lifespan. This preference persists even when compared to gas district heating, which offers a longer lifespan and marginally improved efficiency than traditional separate heating systems but falls behind due to its CO2 emissions. The curve of district heating leveled off earlier, reflecting some residents' collective preference for cheaper, long-lasting district heating. The option to retain existing heating systems, which represent the least financial burden in terms of upfront costs but fail on efficiency and environmental grounds, is the least popular choice.

This outcome may signify an inherent bias within the simulation towards progressive environmental action. The bias is driven by the model's weighting of environmental concerns and a reflection of the agents' social pressure, where the adoption of greener technologies is perceived positively. This underscores the potential effectiveness of policy mechanisms, such as subsidies or carbon taxes, to steer communities towards greener alternatives, despite the associated costs and practicalities.

Moreover, the model offers a valuable tool for evaluating the influence of social norms and financial capabilities on the decision-making process. It highlights the critical role played by community behavior and collective environmental commitment in fostering the adoption of sustainable heating technologies. As such, the findings emphasize the interconnected nature of individual choices and broader community dynamics in the adoption of a more sustainable and environmentally conscious approach to residential heating.

Conclusion

This study applied an ABM to simulate the adoption dynamics of residential heating systems, focusing on gas-free heat pumps and district heating options. The model effectively captures the nuanced decision-making process of households in adopting heating systems. The model highlights the complex interplay between various factors that shape household decisions. It underscores the need for multi-faceted policy instruments that not only encourage the adoption of green technology but also address barriers related to cost and technology longevity.

Future research could focus on refining the model's parameters, building a more comprehensive real-world dataset to capture a broader spectrum of real-world behaviors, and integrating feedback loops that might emerge from widespread adoption of these technologies. Conducting a comprehensive sensitivity analysis is essential for validating the model. Furthermore, while the model captures individual decision-making within a physical neighborhood context—significantly shaped by social norms—it does not explicitly simulate collective decision-making scenarios. Such scenarios could include the influence of key decision-makers whose choices disproportionately impact the community's adoption patterns.

References

Ajzen, I. (1991). The theory of planned behavior. *Organizational Behavior and Human Decision Processes*, *50*(2), 179–211. https://doi.org/10.1016/0749-5978(91)90020-T

Ajzen, I. (2002). Perceived Behavioral Control, Self-Efficacy, Locus of Control, and the Theory of Planned Behavior1. *Journal of Applied Social Psychology*, *32*(4), 665–683. https://doi.org/10.1111/j.1559- 1816.2002.tb00236.x

Blum, P., Campillo, G., Münch, W., & Kölbel, T. (2010). CO2 savings of ground source heat pump systems – A regional analysis. *Renewable Energy*, *35*(1), 122–127. https://doi.org/10.1016/j.renene.2009.03.034

de Wildt, T. E., Boijmans, A. R., Chappin, E. J. L., & Herder, P. M. (2021). An ex ante assessment of value conflicts and social acceptance of sustainable heating systems: An agent-based modelling approach. *Energy Policy*, *153*, 112265. https://doi.org/10.1016/j.enpol.2021.112265

Grimm, V., Berger, U., DeAngelis, D. L., Polhill, J. G., Giske, J., & Railsback, S. F. (2010). The ODD protocol: A review and first update. *Ecological Modelling*, *221*(23), 2760–2768. https://doi.org/10.1016/j.ecolmodel.2010.08.019

Hansen, P., Liu, X., & Morrison, G. M. (2019). Agent-based modelling and socio-technical energy transitions: A systematic literature review. *Energy Research & Social Science*, *49*, 41–52. https://doi.org/10.1016/j.erss.2018.10.021

Hesselink, L. X. W., & Chappin, E. J. L. (2019). Adoption of energy efficient technologies by households – Barriers, policies and agent-based modelling studies. *Renewable and Sustainable Energy Reviews*, *99*, 29–41. https://doi.org/10.1016/j.rser.2018.09.031

Kazil, J., Masad, D., & Crooks, A. (2020). Utilizing Python for Agent-Based Modeling: The Mesa Framework. In R. Thomson, H. Bisgin, C. Dancy, A. Hyder, & M. Hussain (Eds.), *Social, Cultural, and Behavioral Modeling* (pp. 308– 317). Springer International Publishing. https://doi.org/10.1007/978-3-030-61255-9_30

Many Dutch are doing well, but for some, vulnerabilities are accumulating. (n.d.). Retrieved January 12, 2024, from https://www.dnb.nl/en/general-news/dnbulletin-2023/many-dutch-are-doing- well-but-for-some-vulnerabilities-are-accumulating/

Moglia, M., Cook, S., & McGregor, J. (2017). A review of Agent-Based Modelling of technology diffusion with special reference to residential energy efficiency. *Sustainable Cities and Society*, *31*, 173–182. https://doi.org/10.1016/j.scs.2017.03.006

Müller, B., Bohn, F., Dreßler, G., Groeneveld, J., Klassert, C., Martin, R., Schlüter, M., Schulze, J., Weise, H., & Schwarz, N. (2013). Describing human decisions in agent-based models – ODD + D, an extension of the ODD protocol. *Environmental Modelling & Software*, *48*, 37– 48. https://doi.org/10.1016/j.envsoft.2013.06.003

Natarajan, S., Padget, J., & Elliott, L. (2011). Modelling UK domestic energy and carbon emissions: An agent-based approach. *Energy and Buildings*, *43*(10), 2602–2612. https://doi.org/10.1016/j.enbuild.2011.05.013

Netherlands, S. (2023, October 27). *Energy consumptionprivate dwellings; type of dwelling and regions* [Webpagina]. Statistics Netherlands. https://www.cbs.nl/engb/figures/detail/81528ENG

Niamir, L., Filatova, T., Voinov, A., & Bressers, H. (2018). Transition to low-carbon economy: Assessing cumulative impacts of individual behavioral changes. *Energy Policy*, *118*, 325– 345. https://doi.org/10.1016/j.enpol.2018.03.045

OECD. (2023). *How Green is Household Behaviour?* https://www.oecdilibrary.org/content/publication/2bbbb663-en PBL. (2020, October 29). *Klimaat- en Energieverkenning 2020* [Text]. PBL Planbureau voor de Leefomgeving. https://www.pbl.nl/publicaties/klimaat-en energieverkenning-2020

Rahmandad, H., & Sterman, J. (2008). Heterogeneity and Network Structure in the Dynamics of Diffusion: Comparing Agent-Based and Differential Equation Models. *Management Science*, *54*(5), 998–1014. https://doi.org/10.1287/mnsc.1070.0787

Rounsevell, M. D. A., Robinson, D. T., & Murray-Rust, D. (2012). From actors to agents in socio-ecological systems models. *Philosophical Transactions of the Royal Society B: Biological Sciences*, *367*(1586), 259–269. https://doi.org/10.1098/rstb.2011.0187

Schiera, D. S., Minuto, F. D., Bottaccioli, L., Borchiellini, R., & Lanzini, A. (2019). Analysis of Rooftop Photovoltaics Diffusion in Energy Community Buildings by a Novel GIS- and Agent-Based Modeling Co-Simulation Platform. *IEEE Access*, *7*, 93404–93432. https://doi.org/10.1109/ACCESS.2019.2927446

StatLine—Inkomen van personen; inkomensklassen, persoonskenmerken. (n.d.). Retrieved January 12, 2024, from https://opendata.cbs.nl/statline/?dl=D4D1#/CBS/nl/dataset/83931NED/table