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Agent-based modelling of building retrofit adoption in neighbourhoods

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ABSTRACT

Despite the significant energy-saving potential of building retrofits, adoption rates remain low, highlighting a gap in understanding homeowners' decision-making processes. This study addresses the research question: How do techno-economic and socio-psychological decision-making rationales impact energy-efficient retrofitting adoption? To answer this, we develop an agent-based model (ABM) to simulate retrofit decisions, contrasting two approaches: a techno-economic model, which focuses on financial returns, and a socio-psychological model, which considers social influences and personal attitudes. The techno-economic model evaluates factors like technology lifetime and profitability, while the socio-psychological model applies the theory of planned behaviour (TPB), incorporating attitudes, perceived control, and social norms. Applied to the Dutch housing market, our ABM simulates retrofit adoption over 20 years, considering various policy scenarios, including a heat pump subsidy, insulation subsidy, and a ban on gas boilers starting in 2026. The model explores whether homeowners opt for heat pumps or continue using gas systems under different policy frameworks in a generic neighbourhood context, where social interactions and peer influence shape decisions. Our results show that the techno-economic decision-making framework projects higher adoption of heat pumps due to favourable net present values (NPVs) and financial incentives, while the socio-psychological rationale shows a preference for gas boilers, with financial incentives having limited impact. These findings suggest that while financial incentives are effective in driving economically motivated decisions, they may be insufficient when social and psychological factors dominate. This highlights the importance of policies that combine both economic and behavioural considerations to increase retrofit adoption and achieve meaningful energy savings.

1. Introduction

Improving energy efficiency in residential buildings is crucial to mitigating climate change and energy crises, particularly in Europe. With 63.5% of building energy used for space heating [1], there is an urgent need to reduce this through insulation and renewable heating systems, moving away from gas-based supply. This process, known as retrofit, is essential, especially among homeowners, who make up 70% of the EU population [2].

Despite the known benefits, the adoption rates of retrofit measures remain disappointingly low: only 1% per year and even less for deep retrofits[1] [3]. This indicates a significant gap in understanding the decision-making processes of homeowners regarding building retrofits. Traditionally viewed as rational economic decisions (i.e. a homeowner retrofits to save money and chooses the most cost-optimal retrofit measure), recent studies show that psychological and social factors also play a significant role [4–7]. Homeowners often renovate if they perceive it as necessary or as offering an improvement in their quality of life [8–12]. Major barriers to retrofit include complex grant applications, lack of awareness, and cost uncertainty [13,14]. Factors including energy independence, thermal comfort, and environmental impact strongly influence retrofit decisions, while demographic variables have ambiguous effects [4].

Earlier energy system models focused on techno-economic aspects of building decarbonisation [15], providing detailed technological representations for policy support. These models, often using bottom-up approaches, study policy scenarios [16–18], support energy planning [19–21] or evaluate retrofit strategies [22]. These models, however, do not account for homeowners' decision-making processes and the influence of peers on their decisions [23].

With the pressing need for energy transition, integrating social aspects of retrofit adoption has become essential. More recent agent-based models (ABMs) simulate homeowners' decision-making, incorporating psychological and social factors. While most ABMs focus on single tech-

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[1] Energy-efficient retrofits with more than 60% in primary energy savings.

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Nomenclature

δNPV_j^i	Differential Net Present Value (NPV) of retrofit option j for agent i $[EUR]$
η_j	Efficiency of the corresponding heating system (η_{gb}-gas boiler efficiency, $SCOP_{hp}$-seasonal coefficient of performance of heat pump)
λ	Scale parameter of the Weibull distribution
μ	Rate of dynamics (Relative Agreement theory)
$\theta_{h,gn}$	Gain utilisation factor for heating
$\widehat{NPV}_j$	Normalised NPV difference of a package j
a	Lower bound of the random uniform distribution
Att_i	Attitude (Att) of agent i towards energy-efficient retrofitting
b	Upper bound of the random uniform distribution
$c_{hp,j}$	Cost of a heat pump in retrofit package j) $[EUR]$
cx_j	Complexity of the retrofit option j
D_i	Decision to retrofit for agent i (1-Yes, 0-No
e_red	Amount of CO_2 emissions reduction $[kg_{CO_2}]$
es_j	Energy-saving index of a package j
f_{el}	Emission factors of electricity in the Netherlands
f_{gas}	Emission factors of natural gas
H_{hp}	Full load hours of heat pump operation in the Netherlands $[hours]$
I_j	Investment for retrofitting package j $[EUR]$
I_{ref}	Investment for gas boiler $[EUR]$
Int_i	Intention to retrofit for agent i
$Int_{th,i}$	Threshold intention to retrofit for agent i
k	Shape parameter of the Weibull distribution
n	Lifetime of investment $[years]$
N_{ad}	Number of adopter agents
N_{tot}	Number of total agents
NPV_j^i	Net Present Value (NPV) of retrofit option j for agent i $[EUR]$
NPV_{gb}^i	Net Present Value (NPV) of gas boiler replacement for agent i $[EUR]$
$p_{el,t}$	Retail price of electricity, incl. taxes $[EUR/kWh]$
$p_{gas,t}$	Retail price of gas, incl. taxes $[EUR/kWh]$
$P_{hp,j}^i$	Nominal power of the heat pump for each house i an retrofit option j $[kW]$
$p_{j,t}$	Retail price of the corresponding energy carrier at time step t, taxes included $[EUR/kWh]$
PBC_i	Perceived Behavioural Control (PBC) for agent i (i.e. the power that agents perceive over their own action)
$Q_{use,j}$	Annual useful energy for space heating for agent i after retrofit j $[kWh/a]$
$Q_{gn,int}$	Solar heat load during heating season $[kWh/a]$
$Q_{gn,sol}$	Internal heat load $[kWh/a]$
$Q_{H,nd,j}^i$	Annual final energy for space heating for agent i after retrofit j $[kWh/a]$
$Q_{H,nd}$	Building's final energy demand for space heating $[kWh/a]$
$Q_{ht,tr}$	Heat transfer by transmission $[kWh/a]$
$Q_{ht,ve}$	Heat transfer by ventilation $[kWh/a]$
Q_0	Annual useful energy for space heating before retrofit for agent i before retrofit $[kWh/a]$
r	Discount rate
SN_i	Subjective norm (SN) for agent i (i.e.e overall perceived social pressure to engage in the behaviour)
t_{boiler}	Boiler service lifetime $[years]$
t_{house}	Construction year of a house
u	Agent uncertainty (Relative Agreement theory)
U_j^i	Utility that agent i derives from choosing retrofit j
$w_{Att,i}$	Weight of the Att parameter for agent i
w_{cx}	Weight of the complexity parameter
w_{es}	Weight of the energy-saving index parameter
w_{npv}	Weight of the normalised NPV parameter
$w_{PBC,i}$	Weight of the PBC parameter for agent i
$w_{SN,i}$	Weight of the SN parameter for agent i
x	Agent opinion (according to Deffuant's Relative Agreement theory)

nologies [24], predominantly on solar panels (PV) [25–32][2] few take account of retrofit adoption as a package of several energy-efficiency measures, such as insulation and heating system replacement [38,39,23,40]. Many ABM studies consider either heating systems [41–43] or insulation [44,45] adoptions independently. Because heating systems and insulation are interdependent, studying them together is crucial. Heat pumps, for example, clearly perform better in well-insulated houses. Our research contributes to this integrated approach.

This paper introduces an ABM designed to simulate homeowners' decision-making processes in adopting energy-efficient retrofit packages, such as insulation measures and heat pumps, in the context of energy prices and policy interventions. This research compares two decision-making rationales: techno-economic and socio-psychological. The techno-economic framework evaluates factors such as the net present value (NPV), while the socio-psychological rationale incorporates variables like social influence, personal attitudes, and perceived control, following the theory of planned behaviour (TPB). The central research question driving this comparison is: How do these two rationales impact energy-efficient retrofitting adoption?

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

The model is applied to a Dutch neighbourhood, characterised by a high share of homeowners (about 70% [2]) and widespread use of condensing gas boilers [46]. The Dutch government's 2026 mandate for hybrid heat pumps provides a policy backdrop for the analysis [47]. By simulating the decisions of homeowners over a 20-year period, the model captures how retrofit choices evolve under both economic and socio-psychological influences. To investigate these influences in detail, we examine how varying electricity and gas prices impact retrofit adoption. Following this, we explore the effect of three policy instruments currently implemented in the Netherlands: heat pump subsidy, insulation subsidy based on specific measures and a ban on gas boilers due to kick in from 2026 (see Section 3.2). By modelling these scenarios, we assess how individual and combined policies influence retrofit adoption.

The study is set in a neighbourhood context, where social interactions and peer influence significantly impact retrofit adoption. Our previous research [33] found that neighbourhood cohesion and satisfaction are positively correlated with adoption likelihood. Homeowners with a strong sense of belonging are more inclined to follow peers in adopting sustainable technologies. Visible retrofits, such as solar panels or upgraded insulation, act as social signals that encourage others to adopt similar measures [48]. The model simulates these interactions, capturing both social dynamics and financial considerations in deci-

[2] For comprehensive reviews of agent-based models of energy technology adoption, see [24,33–37].

Table 1
Selected building archetypes [56].

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

sion making. This neighbourhood-based approach is crucial because policies—such as financial incentives or information campaigns—are often implemented at the community level. Understanding how economic and social factors interact within neighbourhoods is key to designing effective policies that encourage retrofit adoption.

The remainder of the article is structured as follows. Section 2 presents the methodology of the work, including the agent-based model narrative, assumptions and simulation parameters (Section 2.1) and the detailed description of decision-making strategies (Section 2.2). Section 3 demonstrates the results of the agent-based simulations for the two agent decision algorithms. In Section 4 we discuss the results obtained. This study aims to provide insights that can inform policy and program designs to effectively encourage retrofitting in residential buildings.

2. Agent-based model of building retrofit adoption

An agent-based model (ABM) simulates the actions and interactions of autonomous agents to assess their effects on the system as a whole [49]. Unlike other modelling techniques, ABM models each agent individually, providing a detailed view of agent behaviours and decision-making processes [49–51]. Its flexibility is particularly beneficial in fields like energy transition planning and policy analysis, where diverse actors and behaviours significantly influence system evolution [52,53]. By moving beyond the simplifying assumption of a representative agent, ABMs facilitate interdisciplinary research, capturing the nuances of complex systems, as such offering powerful tools for analysing dynamic, interconnected systems [54].

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

The term “neighbourhood” refers to a group of agents, but it does not imply any geographic or spatial proximity. There are no spatial or vicinity-based rules governing interactions. Instead, agents are connected through a conceptual network where they are considered “neighbours” based solely on their inclusion within the same group. These agents randomly interact with each other to exchange information, which can influence their “attitude” parameter toward retrofit adoption. This abstract structure allows us to capture the diffusion of social influence and decision-making behaviours without relying on physical adjacency or geographic constraints.

The ABM of retrofit uptake proposed in this article is a result of the following distinct tasks, which are explained in detail in Sections 2.1 and 2.2:

1) Definition of buildings, retrofitting packages suitable for these buildings, their respective costs and energy demand data
2) Definition of algorithms or rules by which a homeowner agent makes a decision about renovating own dwelling

The model has been implemented in Python, with the source code publicly accessible on GitHub [55].

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

This section covers building (Section 2.1.1), retrofitting packages (Section 2.1.2), and household energy prices (Section 2.1.3) in De Maten, Apeldoorn, in the Netherlands. This location was chosen for its representative building types (terraced, semi-detached, and detached) from the 1960-85 construction period.

2.1.1. Existing buildings and their current state

Buildings in De Maten are categorised using TABULA typologies [56] based on Dutch national example buildings [57,59]. These archetypes represent buildings from various construction years and include detached, semi-detached, and terraced houses [60]. Energy demands for space heating vary by building type and construction period, with details provided in Table 1. The U-values for the building envelope and glazing, essential for evaluating the thermal performance of the retrofitted buildings, are detailed in the spreadsheet file [61]. The assumed efficiency of both existing and new gas boilers are the same and are provided in Table A.8. Although there are a total of 11,000 dwellings in De Maten [62], we only look at a smaller neighbourhood of 100 buildings.

2.1.2. Retrofit packages

Retrofit packages include an electric heat pump or a condensing gas boiler (GB) and varying insulation levels (deep and moderate [63]), based on Dutch regulations (see Table 2). Double-glazed windows (HR++) are also considered [64]. Detailed description of retrofit packages, including the seasonal coefficients of performance (SCOPs) of corresponding heat pumps, are provided in Table A.7.

Heating energy needs after retrofitting are calculated using the seasonal method per EN ISO 13790:2008. This method calculates the building energy need for space heating ($Q_{H,nd}$) by considering the heat transfer by transmission ($Q_{ht,tr}$) and ventilation ($Q_{ht,ve}$) of the building zone when heated (or cooled[3]) to a constant internal temperature and the contribution of internal ($Q_{gn,sol}$) and solar heat gains ($Q_{gn,int}$) to the building heat balance (Eq. (1)). Many of the assumptions for this calculation, such as window orientation or heating days (i.e. 212 days) are adapted from [65], which are available in [66]. The values of heating energy need after the retrofit and the costs of these packages are provided in the calculation tool [61].

$$Q_{H,nd} = (Q_{ht,tr} + Q_{ve,tr}) - \theta_{h,gn}(Q_{gn,sol} + Q_{gn,int}) \tag{1}$$

The assumptions regarding electric heat pump and gas boiler employed in retrofit packages are presented in the Appendix B.

2.1.3. Technology costs and energy prices

Retrofitting costs (excluding taxes) are based on German cost functions [67] and adjusted to 2022 Dutch market conditions [68,69]. The

[3] Cooling is not considered in this study.

Table 2
Description of the insulation levels.

Insulation	Source	Min. U-values according to legal requirements	U-values applied in the model
moderate	RVO's exemplary [57]	$U_{roof} = 0.29$ $U_{wall} = 0.59$ $U_{floor} = 0.29$	$U_{roof} = 0.28$ $U_{wall} = 0.58$ $U_{floor} = 0.28$
deep	Building Decree 2012 major retrofit (and new construction) [58]	$U_{roof} = 0.17$ $U_{wall} = 0.22$ $U_{floor} = 0.29$	$U_{roof} = 0.16$ $U_{wall} = 0.21$ $U_{floor} = 0.28$
double-glazing	RVO's exemplary [57]	$U_{window} = 1.40$	$U_{window} = 1.20$

Table 3
Household electricity and gas prices in the Netherlands [70].

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

Table 4
Operationalisation of the decision algorithms by stage.

Decision stage	techno-economical decision	socio-psychological decision
1) Consideration	IF current (gas) boiler breaks	IF current (gas) boiler breaks ‖ it is near breakdown ‖ gas prices increase sharply
2) Decision	IF considering, then implement	IF an agent's intention to retrofit > threshold (according to the TPB) (see Section 2.2.2)
3) Selection	choose retrofitting package with max. net present value	retrofitting package with max. utility (see Section 2.2.2)

calculated costs per building archetype and per retrofit package are included in the spreadsheet file [61]. Household gas and electricity prices, given in real 2023 EUR/kWh. Three distinct scenarios are considered, as summarised in Table 3: low electricity prices and high gas prices such as they could be observed in 2019, low electricity prices and high gas prices from 2022 and very high electricity and high gas prices from 2023.

2.2. Decision-making strategies for retrofit adoption

Agent adoption decision rules in ABMs can vary in complexity [37], with retrofit decisions being a complex socio-technical process involving multiple factors and actors [9,45]. As a result, energy-efficient retrofit models often adopt theoretical frameworks from social psychology, such as the TPB [71], or Consumat [72]. TPB is frequently used due to its flexibility and ease of operationalisation via threshold values [34]. In this study, we combine TPB with utility theory, following models in [31] and [26].

TPB was chosen for its effectiveness in explaining behaviour under volitional control, such as retrofit adoption, where attitudes, social norms, and perceived behavioural control drive intentions and actions [71]. It has been widely applied in energy retrofit research, successfully projecting energy-efficient behaviour, including retrofit adoption [85,82]. TPB's flexibility and empirical validation make it ideal for modelling retrofit decisions in ABMs [34,31].

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

1) Consideration: Identifying the need for retrofitting, triggered by heating system failure, end-of-life, or gas price hikes.
2) Decision: Deciding whether to retrofit.
3) Selection: Choosing a retrofit package.

Considering retrofitting occurs when there is a need to replace the current system, which can be triggered in three common cases: the current heating system breaks down, the gas boiler reaches the end of its service life, or there is a sudden increase in gas prices. The first case is a so-called "problem trigger," while the other cases are "opportunity triggers," as homeowners can choose to keep the old boiler [73]. We model these triggers using a Weibull distribution, assuming most condensing gas boilers last around 16 years [74–76]. Once an agent's status is "considering" stages 2 and 3 follow. These stages are operationalised differently in the two decision frameworks. Table 4 summarises the main differences, with detailed explanations in Sections 2.2.1 and 2.2.2.

2.2.1. Techno-economic (or financial) decision-making (FIN)

This decision-making framework, referred to as *"FIN"*, treats retrofitting as a financial decision triggered when the current heating system reaches the end of its service life. Homeowners, acting as financially-driven agents, adopt the retrofit package with the highest positive NPV. The process follows three stages, as shown in Table 4.

The differential NPV in Eq. (2) is the difference between the NPV of the considered retrofit package j and that of the standard gas boiler (gb) replacement (i.e. reference NPV) [77]. For each agent i, NPV_j^i and NPV_{gb}^i are calculated as in Equations (3) and (4) respectively.

$$\delta NPV_j{}^i = NPV_j^i - NPV_{gb}^i \tag{2}$$

$$NPV_j^i = -I_j^i + \sum_{t=0}^{n} \frac{-p_{j,t} \cdot Q_{use,j}/\eta_j}{(1+r)^t} + \frac{L}{(1+r)^t} \tag{3}$$

$$NPV_{gb}^i = -I_{gb}^i + \sum_{t=0}^{n} \frac{-p_{j,t} \cdot Q_0/\eta_{gb}}{(1+r)^t} \tag{4}$$

Where I_j and I_{ref} are the investments for retrofitting package j and gas boiler, respectively; $Q_{use,j}$ is the annual useful energy after retrofit j; $p_{j,t}$ is the energy carrier's retail price at time step t; η_j is the heat-

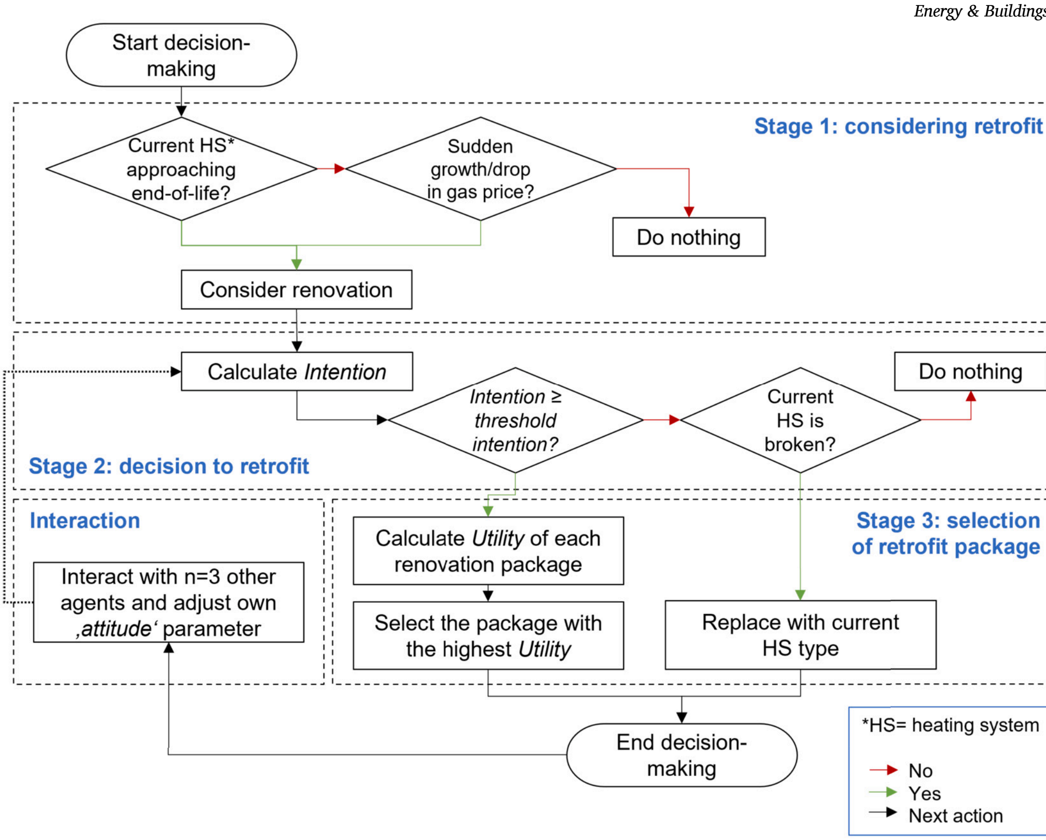

Fig. 1. Flowchart of socio-psychological (SOC) decision-making framework.

ing system efficiency (gb stands for gas boiler); Q_0 is the annual useful energy before retrofit; and r is the discount rate. Insulation and glazing materials have a 30-year lifespan [78], while heat pumps and gas boilers last up to 20 years [74,79]. The NPV analysis time frame is 20 years, assuming a residual value of 33% for insulation technologies.

2.2.2. Socio-psychological decision-making (SOC)

This decision-making framework, referred to as *"SOC"*, integrates social and psychological factors, reflecting that human decision-making is deeply embedded in social contexts. It uses the TPB and includes peer influences. The process follows three stages, as illustrated in Table 4. Fig. 1 is the flowchart of the socio-psychological decision-making process implemented in the current ABM.

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

1) Approaching Breakdown: when T_{cons} years are left until the heating system's expected end of service life ($t = T^i_{hs,l} - T_{cons}$). This indicates the system is losing efficiency or needs more maintenance. The old gas boiler's lifespan is modelled using a Weibull distribution.[4] Further details of this assumption are in the appendix C.
2) Gas Price Increase: in case there is a sharp increase in gas price (compared to the previous year) sufficient to consider replacing the boiler. As [80] demonstrate, present and expected energy costs drive heating system replacements. Further details of this assumption are in the Appendix D.

In Stage 2, the decision to retrofit is based on the TPB, which projects and explains behaviour under volitional control [71]. TPB postulates that behaviours stem from intentions (Int), but can be hindered by factors like time, money, and knowledge. Widely used across various fields, TPB suits retrofit decisions, with empirical evidence linking intention to energy-efficient behaviour [81,82,85]. As shown in Fig. 2, an agent's decision to retrofit $D_i(t)$ depends on whether intention Int_i exceeds the threshold Int_{thr} (Eq. (5)). Intention Int is calculated at each step for each agent i, while the intention threshold Int_{thr} is a calibrated constant (Section 2.3).

$$D_i(t) = \begin{cases} 1, & \text{if } Int^t_i > Int_{th,i} \\ 0, & \text{if otherwise} \end{cases} \tag{5}$$

The intention of agent i to retrofit is a function of attitude towards retrofitting $Att_i(t)$, "Subjective Norm", $SN_i(t)$ and "Perceived Behavioural Control", PBC_i. According to [85], these components significantly project the intention to perform energy efficiency retrofits. The relationship is expressed in Eq. (6), with weights [5] ($w_{Att,i}, w_{SN,i}, w_{PBC,i}$ summing to 1 (Eq. (7)). The three components (Att, SN and PBC) are parameterised, as demonstrated in Fig. 2.

$$I_i = Att_i(t) * w_{Att,i} + SN_i(t) * w_{SN,i} + PBC_i * w_{PBC,i} \tag{6}$$

$$w_{Att,i} + w_{SN,i} + w_{PBC,i} = 1 \tag{7}$$

Attitude toward the behaviour $Att_i \in [0,1]$ is the subjective probability that retrofitting will lead to positive outcomes, such as comfort, reduced energy bills, and lower CO2 emissions [83,4]. It is initialised from a beta distribution and evolves over time through agent interactions. The parameterisation and evolution mechanism of attitude is described in the Appendix E.

Subjective Norm (SN) $SN_i \in [0,1]$ representing perceived social pressure, is conceptualised as the share of adopters in the neighbour-

[4] Weibull distribution is widely used to describe the lifetime distributions of systems [84].

[5] The weights are based on the results of their relative impacts on the intention reported in [85].

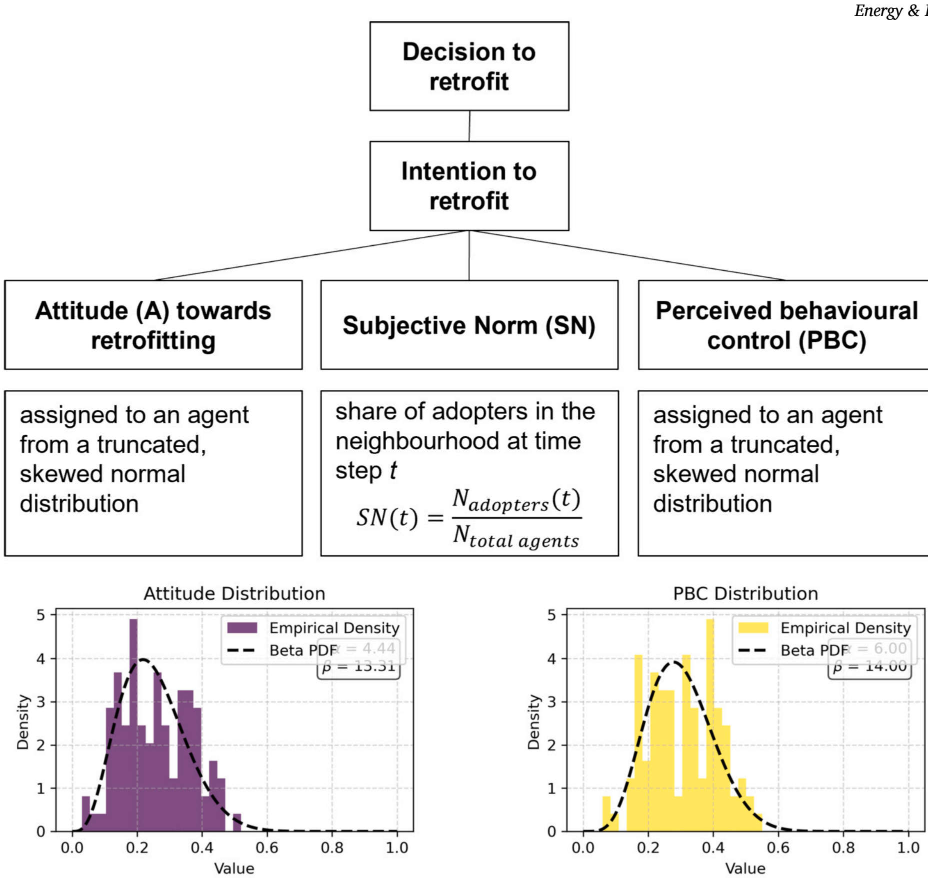

Fig. 2. Operationalisation of the TPB in this ABM.

hood at time t (Eq. (8)). It assumes each agent knows the number of adopters in the neighbourhood, affecting all agents equally.

$$SN_i = \frac{N_{ad}}{N_{tot}} \tag{8}$$

The value of SN_i evolves over time, as it is dynamically updated at each time step based on the cumulative number of adopters. This means that as more agents adopt retrofits within the neighbourhood, the perceived social pressure increases, progressively influencing the behaviour of the remaining agents.

Perceived behavioural control (PBC) $PBC_i \in [0, 1]$ represents an agent's perceived power over their actions. Higher perceived retrofit knowledge and income levels correlate with higher PBC [85]. PBC is initialised similarly to attitude but remains constant over time.

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

$$U_j^i = \widehat{NPV}_j \cdot w_{npv} + cx_j \cdot w_{cx} + Att_i \cdot es_j \cdot w_{es} \tag{9}$$

Complexity serves as an indicator of implementation difficulty and disturbance level, based on the literature and expert knowledge [86,87] (Table F.9). The energy-saving index represents normalised [6] savings in final energy demand for space heating for each package.

[6] min-max technique is used for normalisation.

Table 5
Estimation of heat pump (HP) share in yearly heating system replacement [89,90].

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

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

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

The socio-psychological decision-making framework contains several uncertain parameters calibrated based on known adoption patterns in the Netherlands. Annually, over 400,000 gas boilers are replaced in residential homes [88]. We estimate the share of heat pumps among these replacements, as summarised in Table 5. Heat pump adoptions in 2021 were used as a baseline, with a 57% increase in 2022 [89] and partial data for 2023 [90].

Based on the estimations presented in Table 5, we assume that between 10% and 23% of gas boilers will be replaced with heat pumps annually during 2022 and 2023. Using historical household energy prices from 2022 and 2023 and assuming subsidies for heat pumps and insulation, we simulate the share of retrofit packages that include heat pumps for these years. The share of packages with heat pumps (averaged across 2022 and 2023) for various combinations of mean PBC, intention threshold, and mean attitude is illustrated in Fig. 3. The average of 10% and 23% – 16.5% – guided the selection of parameter values resulting in a 16% share of heat pumps (see the selected parameters in Table A.8).

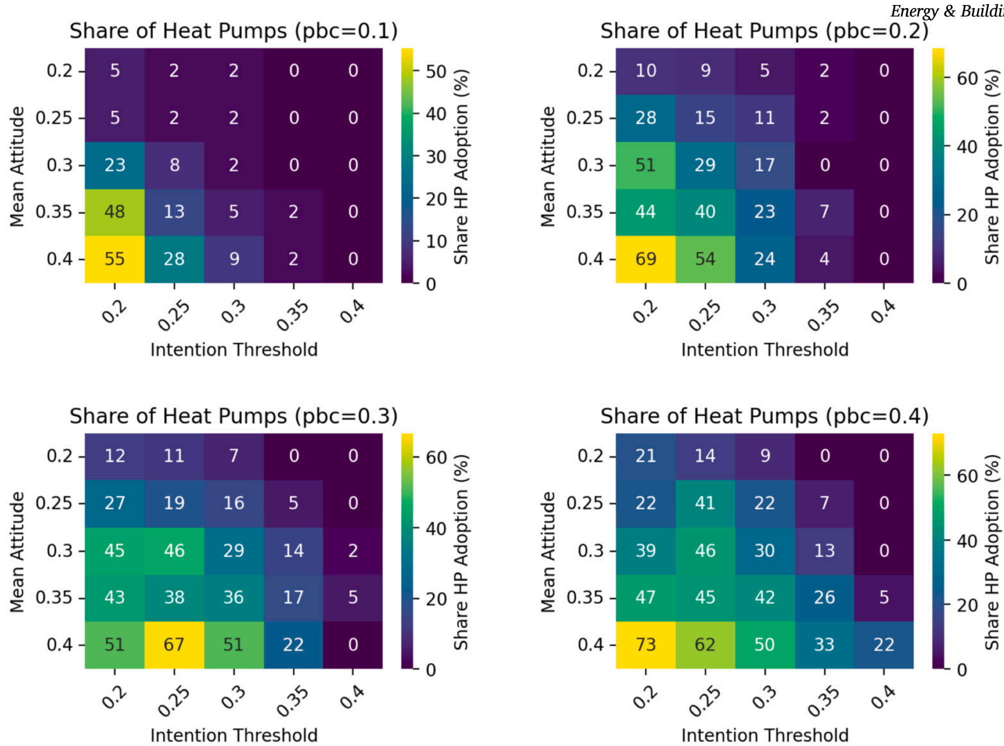

Fig. 3. Calibration results – share of heat pumps in annual heating system replacements (four graphs for four different values of mean PBC among agents). (For interpretation of the colours in the figure(s), the reader is referred to the web version of this article.)

3. Results

This section presents the results of three simulation experiments. Firstly, we examine the adoption of energy-efficient measures at different household electricity and gas prices (Section 3.1). Secondly, we assess the impact of various policies on adoption rates (Section 3.2). Finally, we conduct a sensitivity analysis of key parameters (Section 3.3).

3.1. Adoption patterns under different electricity and gas price scenarios

The simulation results demonstrate varying adoption patterns of energy-efficient measures based on different electricity and gas price scenarios. The adoption of retrofitting packages in the neighbourhood is illustrated in Fig. 4, where the top row presents results for the techno-economic decision-making rationale (*FIN*) and the bottom row for the socio-psychological decision-making framework (*SOC*).

As shown in Fig. 4, under the *FIN, 2023 scenario* (highest gas prices), a complete transition to heat pumps with insulation occurs by 2038. This shift is primarily driven by the significant cost savings associated with these packages. In contrast, the *FIN, 2022 scenario* (lower electricity prices) results in a more diversified adoption pattern: approximately half of the agents choose heat pumps with insulation, while the other half opt for heat pumps without insulation. Even under the *FIN, 2019 scenario* (lowest gas prices), heat pumps with insulation emerge as the most profitable option for half of the agents. The remaining agents either replace their gas boilers with new ones or combine this replacement with wall insulation. This suggests that while heat pumps are still considered a financially attractive option, the lower electricity prices make gas boilers a more viable choice for some. After 2038, the number of insulated gas boilers begins to decline. This shift occurs as the gas boilers initially adopted reach the end of their service life and require replacement. Since these agents have already invested in insulation, they do not need to re-insulate. Consequently, when their gas boilers reach the end of their service life, they select the most cost-effective replacement option available: another gas boiler without additional insulation.

The bottom row of Fig. 4 illustrates the impact of socio-psychological factors on adoption decisions. Across all scenarios, a significant portion of agents opt to renew their existing gas boilers, reflecting a strong preference for the status quo. The *SOC, 2019* scenario, characterised by low gas prices, shows that over 80% of agents preferred to simply renew their boilers, with the remainder selecting one of the alternative options. In the other two scenarios, approximately 40% of agents choose heat pumps: in *SOC, 2022*, these agents opt for heat pumps without insulation, likely due to low electricity prices, whereas in *SOC, 2023*, some agents initially choose heat pumps with insulation but later renew only the heat pumps, foregoing insulation.

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

Fig. 5 presents the cumulative savings in final energy demand for space heating (*left*) and CO_2 emissions (*right*) resulting from the adoption of retrofit packages. The **left panel** demonstrates that financial decision-making consistently leads to greater savings in final energy demand compared to socio-psychological decision-making. This is primarily attributed to the more aggressive adoption of heat pumps with higher SCOPs and deep insulation packages under financial decision-making. The *FIN, 2023* scenario achieves the highest savings, reaching a 90% reduction in initial neighbourhood final energy demand for space heating. In contrast, the *FIN, 2019* scenario, characterised by low gas prices, results in the lowest savings due to a slower transition to heat pumps and a higher prevalence of gas boilers with insulation. The **right panel** illustrates the corresponding CO_2 emissions reductions, which closely follow the trends observed in final energy demand savings. The

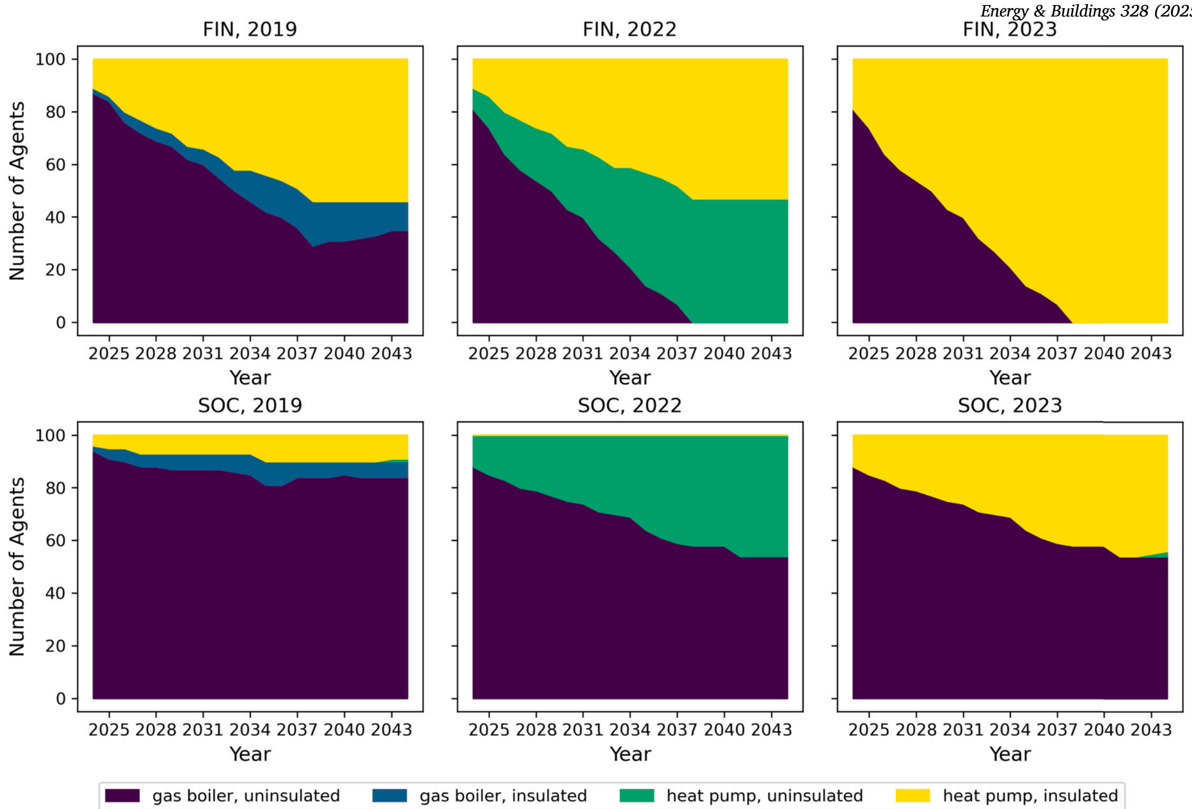

Fig. 4. Heating system and insulation state in the neighbourhood - reference scenario.

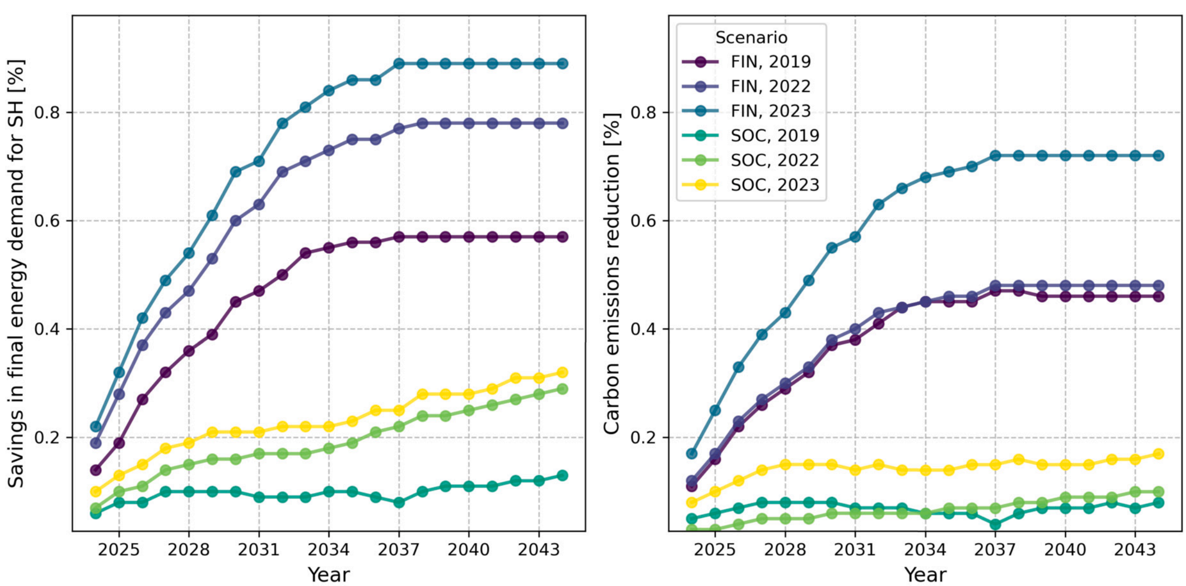

Fig. 5. Savings in final energy demand for space heating (*left*) and CO_2 emissions reduction (*right*).

FIN, 2023 scenario again exhibits the most significant emissions reductions, while the *FIN, 2019* scenario demonstrates the least.

3.2. Adoption patterns under various policy instruments

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

1) heat pump subsidy covering 30% of the purchase price [91]
2) insulation subsidy with the amount shown in Table 6 [92]
3) ban on gas boilers starting from 2026 [93]

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

Fig. 6 shows the detailed breakdown of the final distribution of retrofit packages across different scenarios. *Panel* (*a*) illustrates the reference scenario, where the adoption of heat pumps with insulation is highest under the *FIN, 2023* scenario, followed by *FIN, 2022*. In contrast, gas boilers with insulation dominate the market in the *FIN, 2019* scenario. Panels (*b*), (*c*), and (*d*) will be described in Sections 3.2.1, 3.2.2 and 3.2.3 below, respectively.

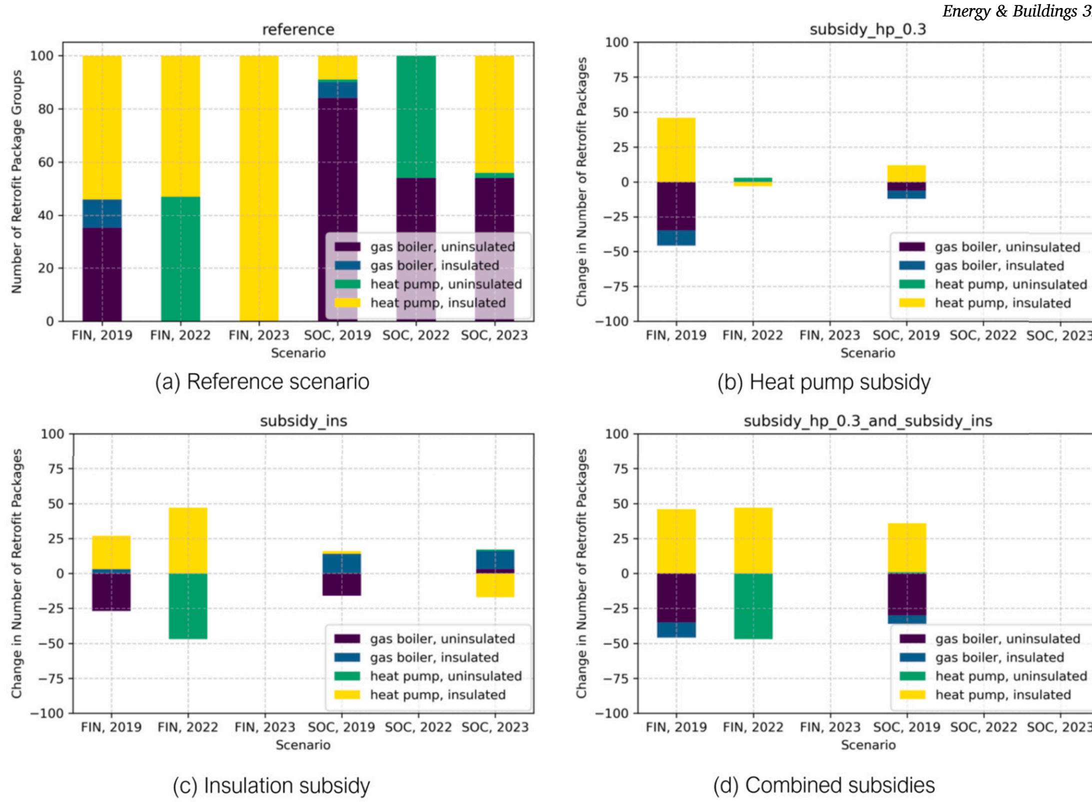

Fig. 6. (a) Number of retrofit packages adopted at the end of the reference scenario. Change in the number of retrofit packages adopted for *(b)* heat pump subsidy, *(c)* insulation subsidy and *(d)* combined subsidies, as compared to the reference case.

Table 6
Subsidy amount for insulation measures of building components [92]. The subsidy values are for implementing two and more measures, the unit is in Euro per square meters of corresponding building element.

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

3.2.1. *Heat pump subsidy*

Fig. 6 (b) highlights the changes in the final mix of retrofit packages when heat pump subsidies are applied, as compared to the reference scenario in Fig. 6 (a). In the *FIN, 2019* scenario, where gas prices are low, the introduction of heat pump subsidies makes heat pumps with insulation the most financially attractive options for most agents, leading to widespread adoption of these technologies.

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

Overall, the results suggest that while heat pump subsidies are effective in promoting adoption based on the techno-economic decision rationale, they do not significantly increase adoption based on the socio-psychological decision framework. Financial incentives alone are insufficient to overcome the social and psychological barriers that many agents face when considering energy-efficient retrofits.

3.2.2. *Insulation subsidy*

Fig. 6 (c) presents the changes in the final mix of retrofit packages when insulation subsidies are introduced, compared to the reference scenario in Fig. 6 (a). Insulation subsidies encourage greater adoption of heat pump and insulation packages in both low gas and low electricity price scenarios of the *FIN* decision rationale. The most notable change occurs in the *FIN, 2022* scenario, where heat pumps with insulation become the most cost-effective option for all agents, leading to widespread adoption. In contrast, in the *FIN, 2019* scenario, only a portion of agents switch to heat pumps with insulation, while others continue to find gas boilers more financially viable.

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

3.2.3. *Combination of heat pump and insulation subsidies*

Fig. 6 (d) illustrates the changes in the final mix of adopted retrofit packages when both heat pump and insulation subsidies are applied, as compared to the reference scenario in Fig. 6 (a). Similar to the results with insulation subsidies alone, this combined intervention prompts a full transition to heat pumps with insulation in scenarios with low gas prices (*FIN, 2019*) and low electricity prices (*FIN, 2022*).

In the *SOC* scenarios, the combined subsidies influence only the scenario with low gas price conditions (*SOC, 2019*). In this case, they lead to a significant increase in heat pumps with insulation (over 30% above the reference scenario), demonstrating a stronger effect than each subsidy applied individually. The minimal changes observed in *SOC, 2022* and *SOC, 2023* across all subsidy scenarios might be attributable to a

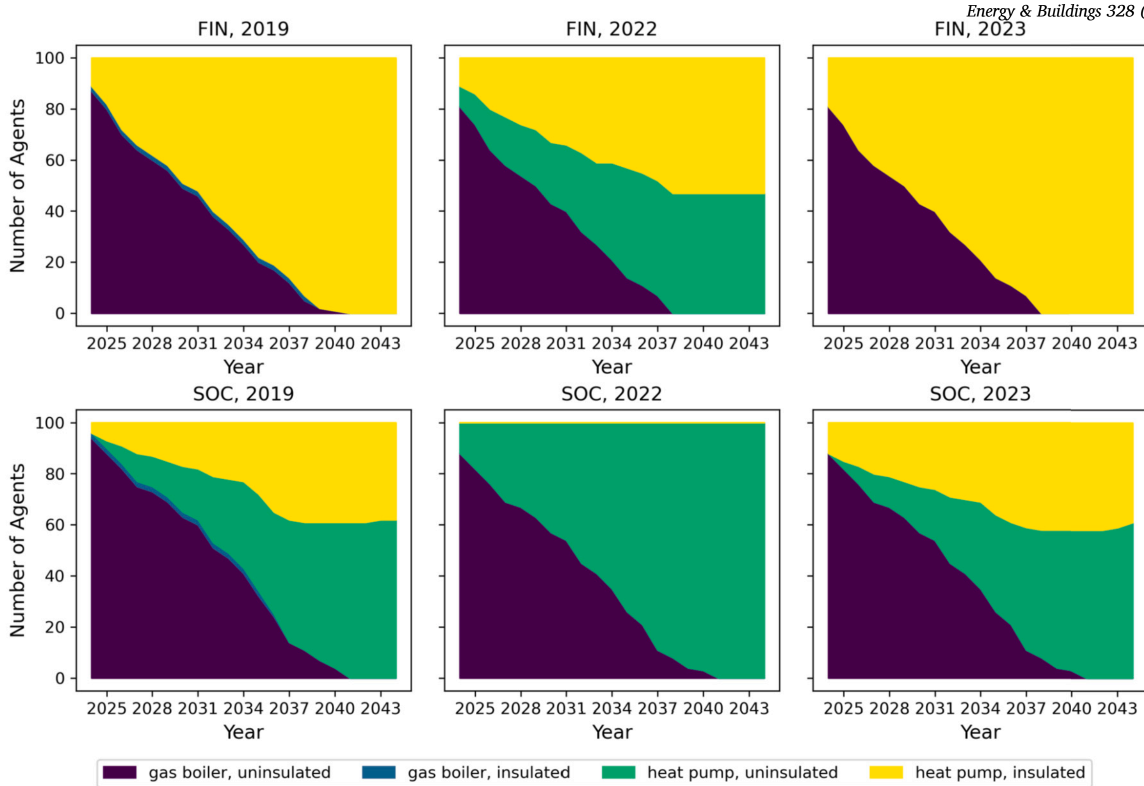

Fig. 7. Heating system and insulation state in the neighbourhood – gas boiler ban scenario.

limit on heat pump adoption, as determined by the calibration of social parameters to cap the share of heat pumps.

Overall, the results suggest that while heat pump subsidies are effective in promoting adoption in the techno-economic decision framework, they do not significantly impact the adoption rate and retrofit package choices in the socio-psychological framework. Hence, this analysis demonstrates that financial incentives alone are insufficient to overcome the social and psychological barriers that many agents face when considering energy-efficient retrofits.

3.2.4. Gas boiler ban

Fig. 7 illustrates the adoption of heating systems and insulation over a 20-year period following the introduction of a gas boiler ban. Based on the *FIN, 2019* and *FIN, 2023* decision frameworks, heat pumps with insulation largely replace gas boilers as the most cost-effective option. In these scenarios, agents are financially motivated to adopt heat pumps with insulation to maximise energy savings. In contrast, under the *FIN, 2022* scenario, where electricity prices are lower, agents predominantly adopt heat pumps without insulation. The lower electricity costs reduce the financial incentive to combine heat pumps with insulation, as the energy savings from insulation do not sufficiently outweigh its additional cost. Consequently, the adoption of heat pumps alone becomes the preferred option in *FIN, 2022*.

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

3.3. Sensitivity of the model to key parameters

This section explores the sensitivity of *SOC* decision-making framework outcomes to several key parameters, including heat pump and insulation costs, mean attitude, perceived behavioural control (PBC), and intention threshold. Figs. 8, 9, and 10 display the resulting effects on heat pump adoption and savings in final energy for space heating when the selected parameters are changed with respect to the values in the reference scenario (percentage change is indicated in the x-axis of the respective figures).

Fig. 8 shows the share of heat pumps adopted with varying heat pump costs. In *FIN, 2019*, even a 25% decrease in heat pump costs leads to a 100% adoption share of heat pumps. In *FIN, 2022*, low electricity costs make heat pumps consistently favourable, with their share remaining unaffected by higher investment costs. However, in *FIN, 2023*, where electricity prices are high, doubling heat pump investment costs results in an 80% drop in their share, as they become a less profitable option. Adoption behaviours in the *SOC* scenarios follow similar trends but are less sensitive to cost changes. For example, a 25% decrease in heat pump costs increases their share among adoptions by only 20%.

Fig. 9 shows the final savings in final energy demand for space heating with varying insulation costs. In *FIN* scenarios, reduced insulation costs lead to higher energy savings, while increased costs result in lower savings. *FIN, 2019* is particularly sensitive, with doubled insulation costs eliminating savings entirely. In contrast, *SOC* scenarios follow similar trends but are much less sensitive to insulation cost fluctuations. An exception is *SOC, 2023*, where reduced insulation costs result in lower energy savings. This might occur because the utility rank of gas boilers with insulation surpasses that of heat pumps with insulation due to high electricity prices, which diminish the appeal of heat pump packages.

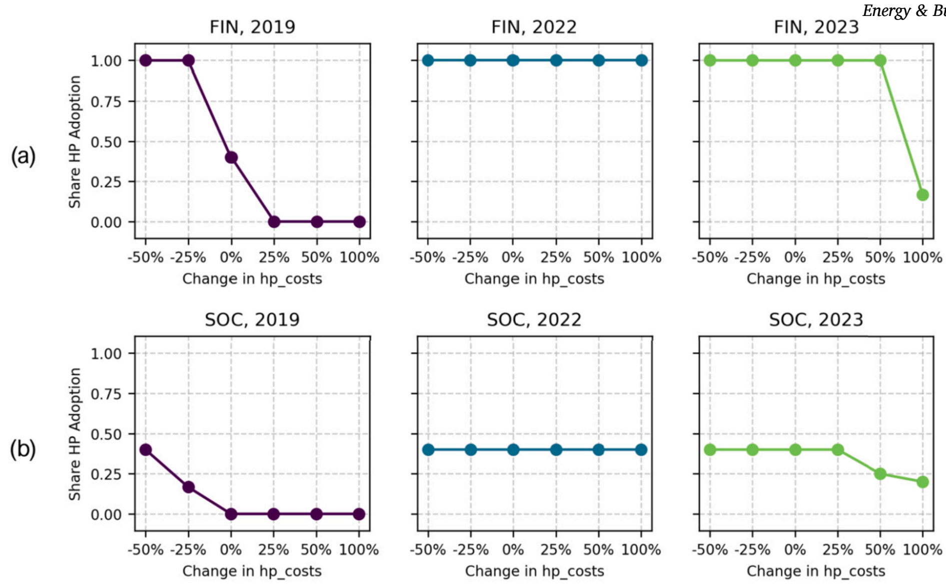

Fig. 8. Share of heat pumps adopted – sensitivity of *(a)* FIN framework and *(b)* SOC framework outcomes to heat pump costs.

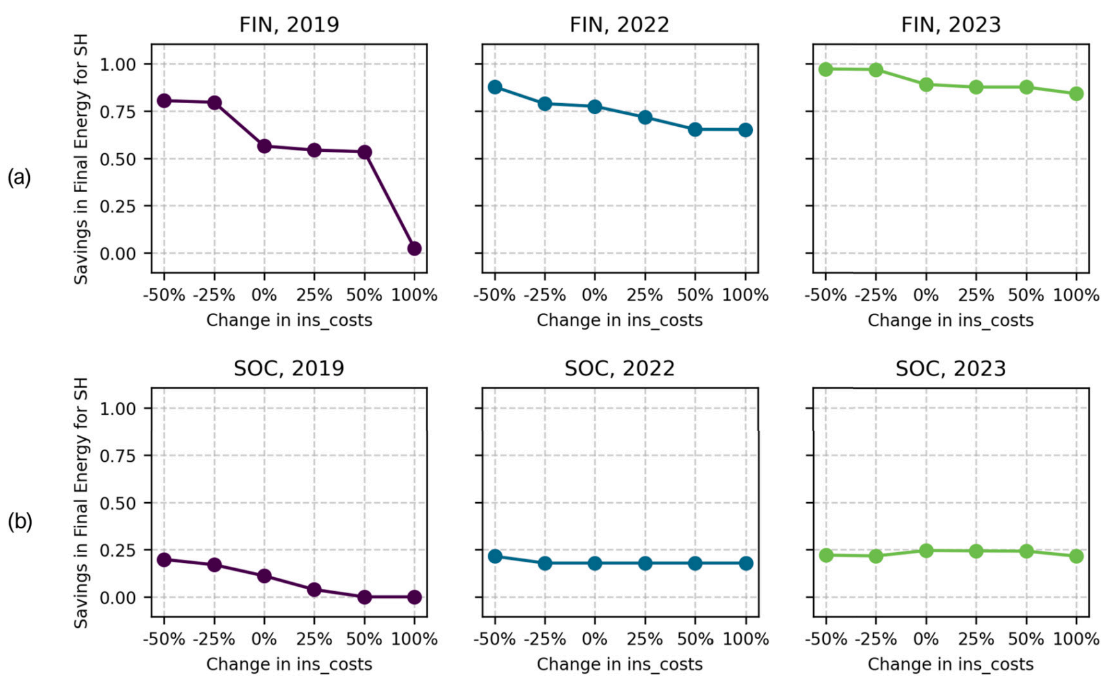

Fig. 9. Savings in final energy demand for space heating (SH) - sensitivity of *(a)* FIN framework and *(b)* SOC framework outcomes to insulation costs.

The *SOC* scenarios are highly sensitive to parameters associated with the TPB: agent attitude, intention threshold, and PBC. Fig. 10 presents the results for savings in final energy demand for space heating in response to variations in these parameters.

As shown in Fig. 10 (*a*), more positive attitudes toward retrofitting significantly increase savings in final energy demand for space heating. This is because more agents are inclined to adopt heat pumps and insulation, driven by their favourable attitudes toward energy-efficient retrofitting.

Fig. 10 (*b*) demonstrates that a lower intention threshold leads to higher adoption rates of heat pumps and insulation, resulting in increased energy savings. In other words, lowering the threshold requirement for intention means more agents surpass the decision-making threshold that leads them to retrofit. Conversely, raising the threshold prevents many agents from adopting energy-efficient measures, thereby reducing overall savings.

Fig. 10 (*c*) indicates that increasing agents' PBC—i.e., their belief in their ability to undertake retrofits—enhances the adoption of energy-efficient technologies and significantly boosts energy savings. This suggests that strengthening agents' sense of control and reducing perceived barriers to retrofitting are crucial for driving widespread adoption of sustainable technologies within the *SOC* framework.

Changes in mean attitude, mean PBC, and intention threshold all similarly affect *SOC* results. Among these, the intention threshold shows the most pronounced effect on adoption rates and energy savings, as lowering it enables more agents to surpass the decision-making threshold for retrofitting. This is followed by agent attitude, where more positive attitudes lead to higher adoption rates. Changes in PBC have a relatively smaller but still significant impact, as they enhance agents' perceived ability to undertake retrofits. Balancing these three variables is crucial (see Section 2.3), although the optimal combination ultimately depends on the expected heat pump adoption rate.

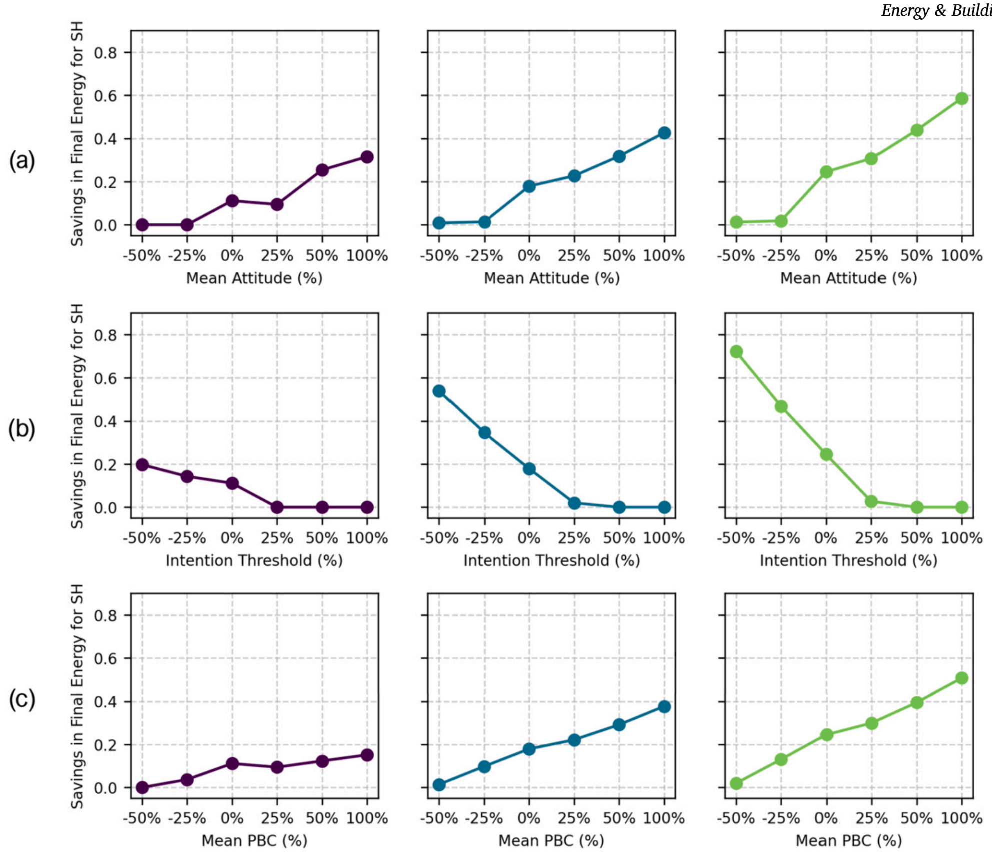

Fig. 10. Savings in final energy demand for space heating (SH) - sensitivity to *(a)* Mean Attitude, *(b)* Intention Threshold and *(c)* Mean PBC in the population.

4. Discussion

4.1. Findings and insights

Rational homeowners evaluating the NPV of retrofit options often transition to heat pumps with or without insulation, especially in older, inefficient houses. This aligns with studies on the cost-effectiveness of energy-efficient retrofits [94,9]. However, the simulation results reveal distinct differences between the techno-economic and socio-psychological decision-making frameworks, offering novel insights into retrofit adoption dynamics. The techno-economic rationale, focused on financial metrics such as NPV, projected higher adoption rates for heat pumps, particularly in scenarios with strong financial incentives and favourable energy prices. These findings reinforce the critical role that financial incentives play in driving retrofits, while also highlighting the limitations of relying solely on financial considerations without addressing behavioural and social factors.

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

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

The policy scenarios tested in our model offer further innovative insights into intervention strategies. While subsidies, as expected, significantly boost heat pump and insulation adoption [95,96] in the techno-economic framework, our results show that these same subsidies have limited impact based on the socio-psychological framework. Here, a ban on gas boilers was more successful in driving sustainable heat transitions. This finding underscores that in contexts where social and psychological factors are barriers, stronger regulatory measures may be required. However, this ban could result in pre-emptive behaviour, with homeowners replacing boilers before the 2026 deadline to avoid future restrictions. This potential unintended consequence, often neglected in previous studies, suggests that timing and communication of regulatory measures must be carefully considered to avoid adverse outcomes.

Furthermore, our results indicate that future gas price expectations and the affordability of heat pumps (which our model does not fully account for) are important factors that could influence decision making. While we did not include detailed affordability assessments, existing low-interest loans in the Netherlands, such as those offered by Warmtefonds, could alleviate financial barriers for some homeowners [97]. Future work should integrate these financial support mechanisms into the model for a more comprehensive analysis of their potential impact.

Energy savings and emissions reductions further reveal the novel contributions of our study. In the financial decision making, the simulations achieved up to 90% savings in final energy demand for space heating, a significant improvement over the 20-25% savings in the socio-psychological rationale. However, these estimates may be overly optimistic due to the exclusion of rebound effects. The rebound effect, where increased efficiency leads to greater energy use, is well-documented in the literature but is not yet integrated into many energy retrofit models [98–100]. Future research should incorporate dynamic models that simulate these effects and explore policy measures, such as stricter post-retrofit energy regulations, to mitigate rebound behaviours.

This study makes several key contributions to the existing literature. Firstly, while most studies focus on single-technology adoption, our research uniquely examines the interdependencies of multi-technology retrofit adoption [41–45,101,102]. Specifically, the decision to adopt a heat pump and insulation is closely linked. Our findings underscore that the effectiveness of a heat pump, measured by its SCOP, is heavily dependent on adequate insulation. Poor insulation significantly reduces SCOP, leading to inefficient heating and failure to maintain desired indoor temperatures [103]. This integrated approach highlights the importance of considering multiple retrofit technologies together, a perspective often overlooked in prior studies.

Secondly, our approach provides a novel distinction between the decision to retrofit and the choice of specific retrofit measures, an area often blurred in the existing literature. While TPB is frequently applied to assess general adoption versus non-adoption decisions, it typically does not address the specific measures homeowners choose [104,105]. Our research fills this gap by mapping out the distinct stages and decision factors that influence not only whether to retrofit, but also which specific measures to adopt. This detailed analysis provides valuable insights for designing tailored policies and interventions that address both the overall decision to retrofit and the selection of appropriate measures.

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

4.2. Limitations and future work

Despite its valuable contributions, this study has several limitations. The lack of detailed empirical data on neighbourhood adoption and social factors, such as attitude and PBC, and the lack of validation for decision-making processes are notable in this regard. Ideally, a dedicated neighbourhood survey would parameterise attitudes, PBC, weights, and intention thresholds, and identify retrofit adopters. This was beyond the scope of our research. The absence of detailed empirical data, especially microdata, is a recognised issue [38]. Although we calibrated input parameters based on historical data, the parameter values are not unique, leading to inherent uncertainty in modelling such complex systems.

The decision-making strategies in this ABM are not exhaustive or fully representative of real homeowner processes. While research in this area is growing, there is no definitive answer to how homeowners decide to renovate or select specific measures. Many authors support the idea that this is a multi-stage process involving numerous factors at each stage [106,24]. Our model considered some decision stages, like retrofit consideration and decision, but omitted the post-implementation stage and feedback mechanisms. The model assumes retrofit is considered primarily when heating systems fail, ignoring renovations for aesthetic reasons or degradation [11], which are harder to estimate. Furthermore, varying the discount rate ‘r’ based on individual financial circumstances could add a more personalised view of the economic impacts on retrofit decisions.

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

Exploring staged retrofits, where improvements are phased, could reflect realistic practices and reveal long-term effects on energy savings [107].

For the calculation of emissions, a constant emission factor for electricity was assumed, although this factor varies depending on the share of renewable electricity in the grid mix [108]. Including a wider array of options and varying emission factors could affect the results and provide a more comprehensive understanding of the potential impacts of different retrofit measures.

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

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

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

5. Conclusion

This study provides valuable insights into the dynamics of energy-efficient retrofitting adoption by integrating techno-economic and socio-psychological decision-making decision rationales. In the techno-economic framework of our model, subsidies play a significant role in encouraging retrofitting by improving financial viability. However, their influence is more limited in the socio-psychological framework, where behavioural factors such as attitudes, perceived control, and social norms have a stronger impact on decision-making. This contrast highlights that retrofitting decisions are not purely financial, as evidenced by the persistent re-installation of gas boilers despite the availability of more sustainable options. Effective policies should not only provide financial incentives but also enhance awareness, simplify grant processes, and address financial barriers through low-interest loans. These findings underscore the importance of combining financial mechanisms with behavioural interventions to support widespread adoption of energy-efficient retrofitting.

Our results underline the interconnected nature of retrofitting decisions, particularly in adopting multi-technology solutions such as heat pumps and insulation. The effectiveness of these technologies, especially heat pumps, is closely linked to complementary measures like

Table A.7
Resume of the retrofit packages.

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

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

insulation, emphasising the need for integrated policy approaches. Furthermore, this research demonstrates that subsidies, while effective in techno-economic contexts, may require augmentation with regulatory measures, such as bans on outdated technologies, to drive significant adoption in scenarios where socio-psychological barriers prevail.

Despite its contributions, this study has limitations, including simplified assumptions about decision-making processes and the exclusion of factors such as rebound effects, varying emission factors, and the influence of additional stakeholders. Future research should aim to address these gaps by incorporating more nuanced models, exploring phased retrofits, and expanding the analysis to include broader geographic scales. Such advancements could improve the realism and applicability of agent-based models for policymaking.

In conclusion, to stand a realistic chance of reducing energy consumption and environmental impact in line with climate and energy goals, economic incentives alone are insufficient. Our results clearly indicate that increasing the uptake of energy-efficient retrofits requires strategies to address the social and psychological factors that play a crucial role in determining intention thresholds.

CRediT authorship contribution statement

Akhatova Ardak: Writing – review & editing, Writing – original draft, Visualization, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Kranzl Lukas:** Writing – review & editing, Supervision, Project administration, Methodology, Investigation, Formal analysis, Conceptualization.

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work the authors used ChatGPT in order to improve the readability and language of the manuscript. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the content of the published article.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Input parameters

Short descriptions of the retrofitting packages included in the ABM are shown in Table A.7. The values of heating energy need after the retrofit and the costs of these packages are provided in the calculation tool [55].

Table A.8
Parameters.

Parameter	Value	Reference
Number of agents	100	
Number of detached + semi-detached houses / terraced houses	0.2	
Value Added Taxes (VAT)	21%	
Gas boiler efficiency	95%	
Heat pump full load hours	1640	[57]
Insulation depreciation time	30 years	
Discount rate	5%	
Investment timeframe	20 years	
Consideration time (T_{cons})	3 years	
Mean attitude	0.25	
Mean PBC	0.3	
Intention threshold	0.3	
Weight of the attitude parameter (ω_{att})	0.47	[85]
Weight of the SN parameter (ω_{att})	0.19	[85]
Weight of the PBC parameter (ω_{att})	0.34	[85]
Opinion dynamics rate (μ)	0.25	
Number of contacts of each agent i ($N_{contact}$)	3	
Emission factor of natural gas (gaseous)	0.203	[109]
Emission factor of electricity in the Netherlands	0.421	[108]

Some input parameters used for the simulation are presented in Table A.8.

Appendix B. Heating system assumptions

Depending on the level of insulation, the heat pump's seasonal coefficient of performance (SCOP) changes (i.e., the better the insulation, the higher the SCOP). The values are estimated based on the work by [110]. We assume that the old central heating radiators are kept, hence there are no additional costs for heat infrastructure acquisition. The nominal power of the heat pump for each house i an retrofit option j, $P^i_{hp,j}$, is calculated by dividing the annual thermal energy need of agent i, $Q_{H,nd,j}$ after retrofit j by the full load hours of operation H_{hp} (see Eq. (B.1)) provided in Table A.8.

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

The specific cost of the heat pump, $c_{hp,j}$, is based on the local market prices for the heat pumps [111] and is derived as a function of its nominal (thermal) power $P_{nom,j}$ (see Eq. (B.2)). The overall costs are provided in [61]. All costs include the Dutch value added tax (VAT) rate of 21% and are real prices, i.e. after it has been adjusted for inflation.

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

Appendix C. Heating system lifetime calculation

The lifetime of an old gas boiler (i.e. condensing, combi gas boiler is a default heating system for all agents at the start) is assumed to be different for each agent and is drawn from the Weibull distribution in Eq. (C.1).

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

where k is the shape parameter, λ is the scale parameter, and t_{boiler} is the random variable representing the boiler lifetime. As we expect the boiler service life expectancy to peak around 16 years, $k = 16$ and $\lambda = 16$. With these parameters, the initial boilers' total service lifetimes are spread as shown in Fig. C.11.

In this model, an agent's current heating system breaks down at some time step. This time is calculated using the assumption that after being constructed, the houses had initially a non-condensing, also known as conventional or low-efficiency, combi gas boiler. This type of system was a standard heating system in the Netherlands between 1960s and 1990s [112]. Since the houses we consider were built between 1965 ad 1991, we assume that all of them had non-condensing boilers first and then switched to condensing or high efficiency boilers after the first boiler broke down (i.e., current heating system at the simulation start). To calculate the time of breaking of the current condensing boiler, we need to make following assumptions.

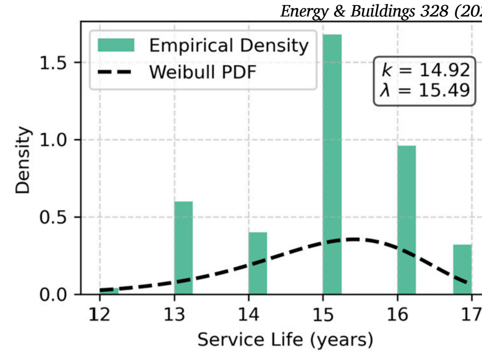

Fig. C.11. A Weibull distribution of condensing gas boilers' service lifetimes.

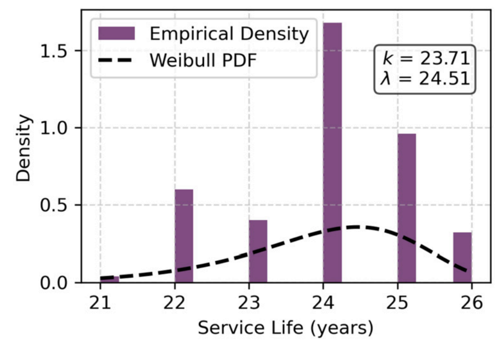

Fig. C.12. A Weibull distribution of non-condensing gas boilers' service lifetimes.

Construction years of agent's houses are set from a random uniform distribution as shown in Eq. (C.2). Here a and b are parameters that define the lower and upper bounds of the distribution (i.e. $a = 1965$ and $b = 1974$ for older buildings, $a = 1975$ and $b = 1991$ for newer buildings); t_{house} is any value within these bounds.

$$f(t_{house}; a, b) = \begin{cases} \frac{1}{b-a} & \text{for } a \leq x \leq b, \\ 0 & \text{otherwise.} \end{cases} \tag{C.2}$$

Service life of a non-condensing boiler is taken from the Weibull distribution similar to the condensing boiler (see Eq. (C.1)), but with different parameters. According to [113], non-condensing boilers last around 25 years (slightly longer than condensing boilers). Hence, non-condensing boilers' total lifetimes are spread as shown in Fig. C.12.

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

In the simulations, some heating systems break already at the initial time steps. Thus, some agents must replace their boilers second time. The time of second replacement is calculated similarly, just by adding the estimated service life of a previously adopted heating system. Another Weibull distribution is created for heat pumps, with the assumption that air-water heat pumps' average service lives are about 15-20 years [79,114]. This distribution is as depicted in Fig. C.13.

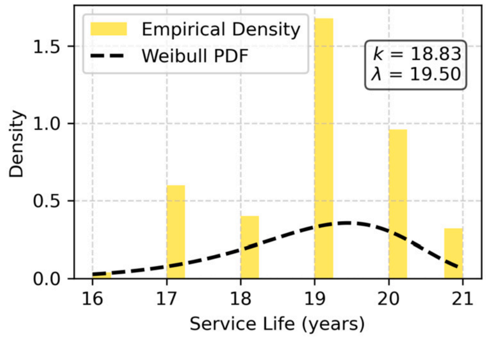

Fig. C.13. A Weibull distribution of air-water heat pumps' service lifetimes.

Appendix D. Price trigger assumption

As [80] demonstrate, present and expected energy costs are one of the most frequently stated drivers for heating system replacements. However, we assume that it is subject to the current operation year of the boiler. That is, if the current heating system is new enough, e.g., 5 years old, then a very high growth in gas prices would be needed to make an agent replace it upon a price spike. Conversely, if a current heating system is older, e.g., more than 10 years, an agent considers replacing it upon even a smaller price growth. This relationship between gas price growth ΔP and threshold age x_{thr} of a current heating system is modelled as in Equation (D.1). Upon a price spike, the current age of a boiler is compared against the threshold lifetime x_{thr} and if it is higher than that, an agent considers retrofitting. The equation is calibrated with the values of $\Delta P = 54\%, x_{tot} = 15, x_{thr} = 11$, which results in $c = 180$.

$$x_{thr} = x_{tot} \cdot \exp \frac{-\Delta P}{c} \tag{D.1}$$

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

Appendix E. Attitude parameterisation and opinion dynamics

Beta distribution is used to parameterise attitude parameter.

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

where

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

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

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

Opinion dynamics sub-model describes how attitude of an agent i changes over time in the simulation. According to [115], Deffuant's relative agreement (RA) model [116] showed superior outcomes, which were very close to the results of the field observations on energy savings derived from eco-feedback program.

In a population of N agents $\epsilon V = 1, 2, ..., n$, each agent has a continuous (real-valued) opinion $x(t) \in (-1, 1)$ and its uncertainty $u \in (0, 2)$. The RA model governs how these opinions and uncertainties are modified upon pairwise interaction of agents. Let us consider that each agent has an opinion segment $s_i = [x_i - u_i, x_i + u_i]$ and $s_k = [x_k - u_k, x_i k + u_k]$. The "relative agreement" of agent i with k (not symmetric) is defined as the overlapping part (Eq. (E.2)) of s_i and s_k minus the non-overlapping part (Eq. (E.3)) divided by s_i (see Eq. (E.4)). The overlap h_{ik} is defined as:

$$h_{ik} = min(x_i + u_i, x_k + u_k) - max(x_i - u_i, x_k - u_k) \tag{E.2}$$

The non-overlapping part is:

$$2u_i - h_{ik} \tag{E.3}$$

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

$$RA = \frac{h_{ik} - (2u_i - h_{ik})}{2u_i} = \frac{h_{ik}}{u_i} - 1 \tag{E.4}$$

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

$$x_k^{t+1} = \begin{cases} x_k^t + \mu \cdot RA^t \cdot (x_i^t - x_k^t), & \text{if } h_{ik}^t > u_i^t \\ 0, & \text{if otherwise} \end{cases} \tag{E.5}$$

$$u_k^{t+1} = \begin{cases} u_k^t + \mu \cdot RA^t \cdot (x_i^t - x_k^t), & \text{if } h_{ik}^t > u_i^t \\ 0, & \text{if otherwise} \end{cases} \tag{E.6}$$

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

Appendix F. Complexity of retrofit packages

Complexity indices are shown in Table F.9.

Table F.9
Complexity of the retrofit packages.

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

Appendix G. Calculation of CO_2 emissions

For each agent i, the amount of CO_2 emissions reduction e_{red} from switching from natural gas-based heating to electricity-based heating is calculated by the Equation (G.1).

$$e_{red}^i = e_{before}^i - e_{after}^i = Q_0^i \cdot f_{gas} - Q_{use,j}^i / \eta_j \cdot f_{el} \tag{G.1}$$

where f_{gas} and f_{el} are emission factors of natural gas (gaseous) and electricity in the Netherlands. The values of the emission factors and the sources are included in Table A.8.

Data availability

I have shared my data online via Zenodo

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