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Agent-based modelling approach to explore efficacy of policies for heat pump uptake

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ABSTRACT

Decarbonising residential heating is essential for the UK to meet its climate targets, as home heating remains a major carbon emitter. This study employs an agent-based model (ABM), integrating logistic regression and utility theory, to simulate UK household adoption of heat pumps from 2021 to 2050. The model captures economic, psychological, and social factors, calibrated with national survey data and historical adoption trends to align long-term diffusion trajectories. Under a business-as-usual scenario reflecting 2025 policies and prices, the model projects 8.7 million households (30.8 %) will adopt heat pumps by 2050. Increasing government grants to £11,500 could raise adoption to 54 %, while a 20 % electricity price reduction may yield a further 12.2 % increase. Logistic regression identifies homeownership, age, cost awareness, and social influence as key predictors. While financial incentives accelerate uptake, they are insufficient alone to meet net-zero targets. Policies must also address behavioural barriers—such as limited awareness, negative perceptions, or perceived hassle—and leverage social networks by promoting peer learning, showcasing early adopters, and supporting community initiatives. This research highlights the utility of ABM for designing decarbonisation strategies that integrate economic, behavioural, and social dimensions of household decision-making.

1. Introduction

The UK is in the midst of a critical energy transition aimed at reducing greenhouse gas emissions and meeting legally binding climate targets. Given that residential heating accounts for approximately 18 % of the UK's total carbon emissions in 2021 (the most recent year for which data are available), the adoption of low-carbon heating technologies is pivotal [1]. Heat pumps, such as air source or ground source heat pumps, are central to decarbonising the residential heating sector [2]. Heat pumps are also recognised as a cornerstone of international climate strategies, featuring prominently in the EU's Fit for 55 package and the IEA's Net Zero by 2050 roadmap [3]. Understanding the factors that influence consumer adoption of heat pumps is therefore not only crucial for the UK but also provides insights into global energy transition challenges, as public acceptability plays a major role in determining the effectiveness of environmental policies. Evaluating the impacts of various policy measures—including financial incentives such as subsidies, and regulatory frameworks such as building codes mandating low-carbon heating in new homes or phasing out gas boilers—is essential to identify barriers and devise strategies that accelerate adoption [3]. This assessment is particularly important as the UK strives to ensure the economic feasibility, social acceptance, and environmental efficacy of its low-carbon heating transition [4].

Heat pump technology, which extracts ambient heat from the air, water, or ground to deliver space and water heating, represents a sustainable alternative to traditional fossil-fuel-based systems [5]. These systems have been commercially available for years and are seeing growing interest across Europe, North America, and Asia, where policy incentives and energy price structures have supported diffusion [3]. Recent data from the UK highlight a slow but steady increase in installations, driven by government support schemes like the Boiler Upgrade Scheme, which offers financial assistance to homeowners who choose heat pumps [6]. Despite their environmental and efficiency advantages, heat pumps currently account for a small fraction of heating systems in existing UK homes. Retrofitting older buildings remains a significant challenge, especially given the higher upfront and installation costs associated with heat pumps [7]. Although recent policy developments aim to increase the uptake of low-carbon heating in new housing—such as the planned ban on gas boilers in new homes from 2025 under the Future Homes Standard—many new builds continue to

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install gas boilers. Therefore, scaling up adoption in older, energy-inefficient homes remains critical to meeting national climate goals. Achieving widespread heat pump uptake is not only critical for the UK to reduce reliance on natural gas and achieve its 2030 and 2050 emissions reduction targets [6], but also serves as a test case for how policy design in one country can inform adoption strategies in others with similar housing stock and institutional constraints.

The electrification of the heat sector through the large-scale deployment of heat pumps is influenced by a complex interplay of economic, social, and psychological factors. Governments across Europe are deploying a variety of policies to offset the financial burden and incentivise adoption [3]. The UK government, for instance, provides grants and low-interest loans to encourage the replacement of conventional boilers with heat pumps [8]. However, economic considerations alone do not fully explain the adoption dynamics. Households may be influenced by non-monetary factors such as perceived comfort, environmental awareness, and peer effects [9,10]. Additionally, technical barriers like the complexity of installation, property-specific suitability, and the disruption caused during the installation process can deter potential adopters [7]. Despite the urgency and policy interventions, there is still limited understanding of how these factors interact and shape heat pump adoption patterns, especially in the UK studies. This paper addresses this gap by firstly combining an ABM approach and logistic regression utility function to simulate and analyse the adoption decisions of UK households, with a particular focus on how different policy measures can influence diffusion and uptake rates.

The remainder of this paper is structured as follows: Section 2 provides a comprehensive review of the literature on heat pump adoption and policy interventions. Section 3 describes the ABM approach, including the data sources and model development. Section 4 presents the simulation outcomes and policy scenarios analysis. Finally, Section 5 concludes with policy recommendations and suggests directions for future research.

2. Literature review

2.1. Policy promotion on heat pumps

Governments across Europe, North America, and Asia are implementing diverse policy instruments to accelerate heat pump adoption, including subsidies, tax incentives, and low- or zero-interest financing options [3]. These measures are typically aligned with national or regional climate targets that require rapid decarbonisation of residential heating. For instance, the European Union's "Fit for 55″ initiative aims to reduce greenhouse gas emissions by 55 % by 2030, partly through increased heat pump deployment across member states [11].

The UK government has implemented several schemes to encourage households and businesses to adopt heat pumps, with the goal of phasing out gas boilers by 2050 [12]. One notable initiative is the Boiler Upgrade Scheme, which provided grants of £7500 for heat pump installations, targeting homeowners who switch from fossil-fuel-based heating systems [13]. Additionally, the Green Homes Grant, which ran from 2020 to 2021, offered vouchers for various home energy improvements, including heat pump installations [14]. These incentives are complemented by VAT reductions for energy-efficient technologies and support for heat pump installer training programmes.

Despite these efforts, the UK faces challenges in achieving significant uptake, especially in existing buildings where retrofitting can be costly and complex. Studies indicate that high upfront costs, installation difficulties, and consumer awareness gaps are key barriers that existing policies have only partially addressed [15,16]. Additionally, while financial incentives have shown positive impacts, concerns remain about the long-term efficacy of these schemes, particularly as subsidies alone may not drive adoption at the required scale [17]. The UK government continues to explore additional policy options, such as low-interest loans and regulatory mandates for new buildings, to bridge these gaps and accelerate the diffusion of heat pumps within both urban and rural areas. Understanding and addressing these challenges is critical for aligning heat pump adoption with broader decarbonisation objectives.

2.2. Application of ABM to study heat pump adoption

Agent-based modelling (ABM) has become an increasingly prominent tool in the study of residential low-carbon technology adoption, particularly heat pumps. ABM is especially useful in this context due to its ability to simulate the diverse decision-making behaviours of individual households and capture the emergent effects of interactions among them. The technology adoption process is not purely economic—it is shaped by social influence, attitudes, behavioural norms, and local policy contexts. ABM enables researchers to represent these complexities explicitly, making it well-suited to support policy evaluation and design.

2.2.1. Overview of recent ABM applications

In recent years, numerous studies have applied ABM to investigate heat pump adoption across various countries, including the UK, Ireland, Germany, Switzerland, the Netherlands, and China. These studies typically model households as agents making decisions based on cost-benefit assessments, social influence, and behavioural predispositions. Most frameworks use utility-based decision rules, where the likelihood of adoption increases if the perceived benefits outweigh the costs. For example, Sachs et al. [18] and Meles and Ryan [19] use economic and behavioural data to represent how households assess financial incentives and peer behaviour. Other studies, such as those by Snape et al. [20] and Nava-Guerrero et al. [21], integrate behavioural theories like the Theory of Planned Behaviour (TPB) or Bounded Rationality (BR) to better represent the psychological factors influencing decision-making.

A consistent finding across these models is the importance of financial incentives and peer effects in driving adoption. Financial aspects—such as subsidies, renewable heat incentives, operational savings, and payback periods—are shown to be major motivators. Several models simulate the role of these incentives in reducing adoption barriers and accelerating diffusion [22–24]. Meanwhile, the role of social influence is commonly operationalised through network models or spatial proximity, with studies demonstrating that households are more likely to adopt heat pumps when their peers or neighbours have done so [18,20,25]. Some studies, like Busch et al. [26], also explore group decision-making within homeowner associations or municipal bodies, revealing the impact of collective preferences and institutional dynamics.

ABMs also vary in terms of the spatial and temporal scales of analysis. While some focus on neighbourhood or municipal levels, others model national-scale adoption under different policy or market scenarios. Brodnicke et al. [24], for instance, simulate the diffusion of heat pumps across Switzerland under combined subsidy and carbon-tax policies, while Derkenbaeva et al. [25] apply the Consumat meta-model to examine household energy transitions in Amsterdam, capturing heterogeneity in decision heuristics. Similarly, van der Kam et al. [27] extend ABM applications to the co-adoption of low-carbon technologies in Switzerland, integrating affective and cognitive factors alongside economic and social dimensions to evaluate how policy mixes influence multi-technology uptake. Chen et al. [28] and Tabatabaei et al. [29] further demonstrate how ABMs can be coupled with predictive control and stochastic optimisation to simulate dynamic energy demand and technology diffusion, enhancing understanding of system-level interactions.

Data sources used to parameterise and validate ABMs differ across studies but commonly include household surveys, census data, energy consumption statistics, and historical adoption trends. For example, Sachs et al. [18] and Lee et al. [23] draw on detailed socio-demographic data and attitudinal surveys, while Snape et al. [20] use installation records to validate predicted uptake. Studies often conduct sensitivity analyses or scenario comparisons to examine how changes in policy, market conditions, or social dynamics influence model outcomes. However, many ABMs remain context-specific and limited in scalability due to their reliance on localised data or simplified behavioural assumptions. Table 1 provides a summary of the above-mentioned 15 ABM applications in heat pump adoption research.

Table 1
Recent ABM applications in heat pump adoption research (15 recent journals).

Article	Research Purpose	Region	Agent(s)	Method for DMR	Factor in DMR	Data for DMR calibration/ validation	Theories under DMR	Model Application
Brodnicke et al. [24]	Residential adoption of HPs	Switzerland	Households (buildings)	Utility-based probability function	Economic and social	Historical Swiss adoption data	–	Policy evaluative, sensitivity analysis
van der Kam et al. [27]	Co-adoption of low-carbon techs	Switzerland	Households	Utility function	Economic, social, psychological	Survey data	Risks-as-feelings framework	Policy mix evaluation and scenario testing
Derkenbaeva et al. [25]	Homeowners' energy efficiency decisions	Amsterdam	Homeowners, tenants	Consumat meta-model decision rules	Economic, social, psychological	Dutch housing survey	–	Policy evaluation, scenario analysis
Meles and Ryan [19]	Residential adoption of HPs	Ireland	Households	Utility function	Economic, psychological, and social	National survey, historical adoption data, Secondary data for heating techniques	TPB	Prediction, policy evaluation, and sensitivity analysis
Article	Research Purpose	Region	Agent(s)	Method for DMR	Factor in DMR	Data for DMR calibration/ validation	Theories under DMR	Model Application
Nava-Guerrero et al. [30]	Group decision on HP adoption	The Netherlands	Individual households and those within HOAs	Utility function	Economic, environmental, spatial and temporal	Secondary data for heating techniques	STS, CAS, and BR	Prediction, policy evaluation
Nava-Guerrero et al. [21]	Individual and group decision	The Netherlands	Individual households and those within HOAs	Lifetime cost calculations	Economic, social and technical	Secondary data for heating techniques	STS and CAS	Prediction, policy evaluation
Chen et al. [28]	Estimate electricity loads	China	Households	Stochastic probability function	Environmental and social	Survey data and real-time monitoring of heat usage	CAS	Prediction
Hall and Geissler [31]	Load control	Switzerland	(Individual and cluster) buildings, and market coordinator	Optimisation function based on conditions of flexibility offers	Technical, energy loads, comfort from building temperature	Smart meter profiles, and secondary data on heating techniques	DSM	Scenario-based prediction
Hall et al. [32]	Load control	Switzerland	(Individual and cluster) buildings, and market coordinator	Optimisation function based on conditions of flexibility offers	Technical, energy loads, comfort from building temperature	Smart meter profiles, and secondary data on heating techniques	DSM	Scenario-based prediction
Sachs et al. [18]	Low-carbon techniques adoption	The UK	Consumer segments	Multi-objective functions	Economic, environmental, social, psychological	National surveys and reports	BR	Prediction, sensitivity analysis
Felten et al. [22]	Load control	Germany	Flexible and inflexible consumers, producers, and grid operators	Predictive control mechanism	Economic, technical and psychological	Real grid data, secondary data on heating techniques	DSM	Policy evaluation, sensitivity analysis
Article	Research Purpose	Region	Agent(s)	Method for DMR	Factor in DMR	Data for DMR calibration/ validation	Theories under DMR	Model Application
Busch et al. [26]	Accelerate local energy infrastructure	The UK	Local authorities, commercial developers, and community organisations	Muti-stage development process and distinct decision heuristics	Institutional, social and economic	Participatory workshops, statistical and geospatial data	STS	Prediction, policy evaluation
Snape et al. [20]	Private adoption of HPs	The UK	Households	Utility function	Economic, social and psychological	National surveys and reports	BR	Sensitivity analysis
Lee et al. [23]	Domestic energy reduction	The UK	Homeowners	Utility function	Economic, Psychological and technical	National surveys	BR	Policy evaluation
Tabatabaei et al. [29]	Energy usage evaluation	The Netherlands	A heating agent and a thermostat agent	Customised mathematical equations	Environmental, and technical	Monitoring data from the test house	–	Scenario-based evaluation

Table 1 summarises 15 recent agent-based modelling studies on heat pump adoption, including research context, agent characteristics, decision-making methods, data sources, and model applications.

2.2.2. Our contributions

Building on this literature, our study makes several novel contributions. First, we develop an ABM tailored specifically to the UK context, simulating household adoption of heat pumps from 2021 to 2050. Unlike many prior models that focus on short-term dynamics or regional case studies, our model provides long-term insights aligned with national decarbonisation goals.

Second, our model features a three-dimensional decision-making framework that combines economic, psychological, and social utilities. These utilities are weighted using empirical data derived from a nationally representative UK survey and calibrated using logistic regression analysis. This integration of statistical modelling with behavioural simulation enhances the robustness and realism of our adoption model.

Third, we calibrate our model against historical UK heat pump installation data (2009–2024) and validate its long-term trajectory using comparative adoption trends from Sweden. This dual calibration approach addresses the limitations of relying solely on early UK data, which predominantly reflects early adopters. By referencing a mature market like Sweden, we improve the plausibility of our long-term projections.

Fourth, we explicitly represent household heterogeneity in terms of income, housing type, social connectivity, and willingness to adopt. We also model peer influence through a social circle mechanism, reflecting the structure of real-world social networks. This allows us to simulate how adoption decisions are shaped by not only individual preferences but also broader community dynamics.

In summary, our work advances the application of ABM to heat pump adoption by integrating robust behavioural data, long-term calibration, and social network dynamics. It provides policymakers with a nuanced tool to explore the impacts of financial and behavioural interventions, identify adoption barriers, and design strategies that support equitable and widespread uptake.

3. Model description and materials

This section describes the agent-based model following the Overview (Sections 3.1–3.3), Design Concepts (Section 3.4), and Details (Sections 3.5–3.8) (ODD) protocol [33].

3.1. Purpose

The model simulates the diffusion of residential heat pumps in the UK from 2021 to 2050. It examines how economic affordability, psychological attitudes, and social influence interact to shape household adoption decisions and how policy interventions (grants and electricity price changes) alter adoption trajectories.

Fig. 1 visualises the overall methodological framework of the study. The model is developed within the framework of the TPB (Section 3.4.1). It begins with national household survey data as the primary input (Section 3.6), which informs the construction of household agents' decision-making rules that incorporate economic, psychological, and social interaction utilities (Section 3.7). The agent-based model is calibrated and validated using historical adoption data from the UK and Sweden (Section 3.8). Finally, the calibrated model is used to simulate heat pump adoption trajectories from 2021 to 2050 and to evaluate the impacts of varying grant levels and electricity prices on adoption outcomes (Section 4).

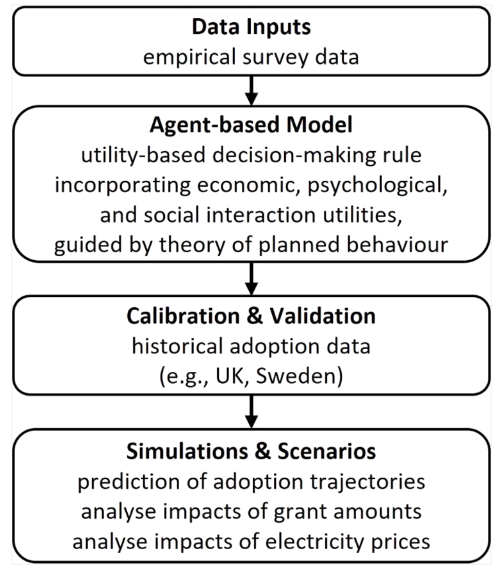

Fig. 1. The model development progress.

3.2. Entities, state variables, and scales

In our agent-based model, households are represented as agents that decide whether to install a heat pump in their homes. Agents are classified as "adopters" if they have already installed a heat pump, while those still using gas, oil, resistive heaters, or solid fuels for heating are termed "potential adopters" [34]. Once an agent adopts a heat pump, we assume they will remain in that status, as the high initial investment is typically offset by long-term energy savings, making reversion unlikely and streamlining the model. A potential adopter will opt for a heat pump installation when the perceived benefits surpass a certain threshold.

Each agent is characterised by a set of attributes that directly reflect the ONS survey microdata (Section 3.6), including socio-demographic factors (gender, age, education), housing type (detached, semi-detached, terraced, flat), tenure status (own, rent, part-own), household income, primary heating system, and psychological variables (attitudes toward heating technologies and replacement intentions). Other state variables include social network connections (Section 3.4.2) and adopter status (e.g., adopter and non-adopter).

Our agent-based model is implemented using AnyLogic 8.9.3, a Java-based simulation platform [35]. Our simulation runs annually from 2021 to 2050 (30 time steps).

3.3. Process overview and scheduling

At each annual time step t, each potential adopter evaluates whether to adopt a heat pump. First, the agent computes its economic, psychological, and social interaction utilities. These are then combined into a total utility value. The agent's total utility is compared against its adoption threshold, which is drawn from a normal distribution with a standard deviation 0.33 with means reflecting empirically observed group heterogeneity of willingness-to-adopt categories. Adoption occurs if the total utility exceeds the threshold and the annualised upfront cost does not exceed 50 % of the household's disposable income (Section 3.7). The model assumes zero residual value for existing heating systems, because system age was not available in the survey dataset; therefore, adoption decisions are based solely on the comparative utilities rather than equipment replacement cycles.

3.4. Design concepts

3.4.1. Theoretical foundation

The decision-making structure in this model is grounded in the Theory of Planned Behaviour (TPB) [36], which explains technology adoption behaviour across diverse contexts [19,37]. TPB posits that an individual's intention to adopt a new technology is shaped by three components: attitude toward the behaviour, subjective norms, and perceived behavioural control. These components map directly onto the psychological, social, and economic utilities in our agent-based model. The economic utility reflects perceived behavioural control and captures households' perceived ease or difficulty of adopting a heat pump, primarily influenced by financial affordability and expected long-term operating costs. The psychological utility represents attitude toward the behaviour and reflects how households evaluate the desirability of heat pump adoption based on perceived benefits such as comfort, efficiency, and environmental impact, as well as perceived drawbacks such as installation disruption or uncertainty in performance. The social utility corresponds to subjective norms and captures the influence of an agent's social network, whereby adoption becomes more likely when peers, neighbours, or acquaintances have already adopted. These interactions operate through information sharing, reduced uncertainty, and reinforcement of group norms (e.g., word-of-mouth diffusion and herd behaviour). Together, these three utility components determine each household's adoption decision in the model (details in Section 3.7).

3.4.2. Agent interaction

In our model, agents influence each other through social circle models (see the model details on social interaction utility in Section 3.7). Social circle model is one of the common approaches to measure social interactions [38,39]. The model typically categorizes an individual's social network into concentric circles, each representing different levels of closeness and influence, from immediate family and close friends to acquaintances and broader community members. This model allows for the assessment of how information, behaviours, and influences spread across these layers, highlighting the varying impact of interactions based on the strength and proximity of social ties. The approach has been adopted by Meles and Ryan [19] to construct social networks of household agents, assisting in investigating how social interactions can influence the decisions of Irish households to adopt a heat pump. Additionally, Hassouna [40] has applied the similar approach to study the influence of social interactions in customer retention in the UK mobile market.

3.4.3. Stochasticity

Stochasticity in the model arises primarily from this random assignment of social networks and the probabilistic nature of adoption decisions. Stochasticity also rises in adoption thresholds (normally distributed within behavioural groups) and simulation replications (30 runs per scenario with different random number generator seeds).

3.5. Initialization

The simulation is initialised to reflect the empirical conditions observed in 2021. It starts by generating a population of 3706 household agents, each corresponding to a unique respondent from the 2021 ONS Public Attitude Tracker dataset [41]. Corresponding to the MCS UK heat pump installation statistics [42], 29 out of 3706 agents are assigned as initial adopters, while all others begin as potential adopters. As the agent population is directly initialised from the survey microdata, the empirical joint distribution of these variables is preserved. This ensures that correlations between attributes (e.g., income and homeownership, education, and environmental attitudes) are maintained rather than artificially imposed or assumed to be independent. Many of these agent attributes are treated as fixed throughout the simulation for simplification, though future extensions could incorporate dynamic socio-economic transitions.

The household agents are randomly distributed within the simulation environment to form a synthetic social network. Social connections between agents are modelled using a social circle approach, where the number of ties follows a normal distribution with a mean of 4 and a standard deviation of 2. The network distribution is consistent with the findings from Wave 3 of the Understanding Society Census, which reports that UK citizens typically have 2 to 6 close friends [43].

3.6. Input data

The model draws on multiple empirical data sources as summarised in Table 2.

These data listed are applied to parameterise agent characteristics, estimate heating costs, and to calibrate adoption dynamics. Household-level socio-demographic attributes, dwelling characteristics, heating systems, and attitudes toward heat pump installation are taken directly from the ONS Public Attitudes Tracker [41], which provides the microdata used to initialise agents and estimate the psychological utility component via logistic regression. Estimates of annual heating expenditure for different fuel types are obtained from GOV.UK domestic energy expenditure statistics [44] and are used to compute the economic utility. Model calibration uses MCS heat pump installation statistics for the UK (2009–2024) [42] to match the recent historical trend in adoption. To overcome the limited time span of UK data, long-term diffusion dynamics are validated against Swedish national heat pump adoption data (SKVP 1993–2022) [45], which provides a mature-market benchmark. Grant levels and electricity price variations [46–50] enter the model as scenario-specific policy inputs. Details on the household survey data and distributions are provided in Appendix A for model outcome replications.

3.7. Submodels

3.7.1. Overall utility

The total utility for each household agent i at time t, represented as, $U_{i,t}$, is calculated as the sum of the weighted partial utilities associated with economic, psychological, and social interaction factors, as detailed below.

$$U_{i,t} = w_{econ} * U_{econ,i,t} + w_{psychology} * U_{psychology,i,t} + w_{network} * U_{network,i,t} \quad (1)$$

where, $\sum_k w_k = 1$ for $k \in \{economic, psychology, social\}$ and w_k, $U_{k,\ i,\ t} \in [0,\ 1]$. The time index t reflects the annual evaluation of policy conditions and agent states throughout the simulation period (2021–2050).

The partial utility obtained from each of the three factors is normalized to lie within the [0, 1] range. As a result, the total utility for a potential adopter also falls within this interval. The weights w_k assigned to the partial utilities of each factor are established through model calibration based on historical heat pump adoption data. In the following subsections, we describe the calculation of the utility for each of these three factors.

3.7.2. Economic utility

In our model's economic decision-making process, each household agent compares the yearly heating costs of their current system with

Table 2
Input data sources and applications.

Source	Application
ONS Public Attitudes Tracker (2021) [41]	Agent attributes + psychological regression
GOV.UK domestic energy expenditure (2021) [44]	Operating cost estimates
MCS UK heat pump installation statistics (2009–2024) [42]	Calibration and short-term validation
SKVP Sweden heat pump statistics (1993–2022) [45]	Long-term diffusion pattern validation
Energy prices [46–49]	Operating cost estimates + sensitivity analysis
Grant amounts [50]	Operating cost estimates + sensitivity analysis

Table 2 provides an overview of empirical data sources used to parameterise agent attributes, estimate heating costs, and calibrate and validate the model adoption dynamics.

those of a heat pump system at time t. These costs include annualized upfront investments with installation fees, applicable grants, and annual operating expenses. For their existing systems, the initial capital costs are treated as sunk costs. The annualized upfront cost of the heat pump system ($AC_{HP,i,t}$) for agent i at time t is determined using Eq. (2), forming the quantitative basis for assessing whether the agent perceives adoption to be financially feasible.

$$AC_{HP,i,t} = \frac{(C_{i,t} - Grant_{i,t}) * r * (1+r)^L}{(1+r)^L - 1} \tag{2}$$

Where, $C_{i,t}$ represents the total upfront installation cost of a heat pump for household i at time t, which varies according to dwelling characteristics and system type. $Grant_{i,t}$ denotes the financial support or subsidy available to household i at time t, which reduces the initial investment. The parameter r is the discount rate used to annualise the capital cost over the system's lifetime. In this model, we assume that households face no interest charges on the financing of installation costs, and therefore treat the loan as interest-free. A detailed justification of the variable values relevant to Eq. (2), as well as to the Eqs. 3(a) and 3(b) below, have been provided in Appendix B.

In our analysis, we utilise the annual domestic energy bills indicating average expenditure each week on fuel per consuming household in the UK reported by GOV.UK [44], to estimate the operating costs of their current heating systems. We then compare these figures with the projected annual costs of switching to a heat pump system using Eqs. (3a) and 3b

$$\begin{aligned} A_{Cost\ HP,i,t} \ &= AC_{HP,i,t} + (1 - bill\ saving) * annual\ heating\ bill_{i,t} \\ &\quad *(1 + \%\Delta\ in\ electricity\ price_{i,t}) \end{aligned} \tag{3a}$$

$$A_{Cost\ exisiting\ system,i,t} = \ annual\ heating\ bill_{i,t} * (1 + \%\Delta\ in\ fuel\ price_{i,t}) \tag{3b}$$

Heat pump systems offer significantly lower annual operating costs compared to conventional fossil-fuel-based and resistive heating systems, with potential cost savings reaching up to 70 % [19]. Empirical estimates suggest that ASHPs achieve average savings of approximately 30 %, whereas GSHPs can realise savings of around 50 %. In this study, a mean value of 40 % bill savings is assumed for heat pumps relative to traditional heating systems. Because heat pump systems rely on electricity to function, our cost calculations also include both the percentage change in electricity prices (%Δ in electricity price) and in alternative fuel prices (%Δ in fuel price).

In addition, we incorporate a prior technical assessment fee of £200 for heat pumps [51]. Consequently, the economic partial utility for agent i at time t is derived as shown in Eq. (4).

$$U_{econ,i,t} = \ A_{Cost\ existing\ system_{i,t}} \Big/ A_{Cost\ HP,i,t} \tag{4}$$

The economic utility value is scaled between zero and one, where a higher value signifies that the calculated costs of the current heating system are comparatively greater than those of a heat pump. This increases the likelihood that an agent will opt for installing a heat pump at home.

3.7.3. Psychological utility

In our agent-based model, we employ logistic regression analysis to interpret survey responses to statements assessing psychological constructs, deriving parameters for the psychological partial utility. The survey gathered information on respondents' intentions to replace their existing heating system and their primary considerations for doing so, such as saving money on heating bills, switching to a more environmentally friendly system, or opting for a more reliable one. Additionally, the survey explored respondents' experiences with their current heating systems and the reasons they pay varying degrees of attention to heat usage—ranging from minimal to significant focus. Following Osborne's (2015) methodology, the logistic regression model is expressed as Eq. (5):

$$P_{i,t}(replacement = 1) = \ 1 \Big/ 1 + e^{-\left(\beta_0 + \ \sum_{k=1}^{n} \beta_k X_{i,k,t}\right)} \tag{5}$$

Here, *replacement* represents respondents' intention to replace their current heating system, with a value of 1 indicating "yes" and 0 indicating "no". $P_{i,t}(replacement = 1)$ denotes the probability that household agent i would consider replacing their current heating system at time t. $X_{i,k,t}$ are the predictor variables k for agent i at time t (e.g., primary reasons for replacement and attention paid to heat usage), while β_k are the coefficients derived from the survey data.

3.7.4. Social interaction utility

In our study, a social circle model is applied to construct the social networks for household agents. Consequently, the partial utility derived from social networks is calculated as follows:

$$U_{soc,i,t} = \ \frac{N_{ia,t}}{N_i} \tag{6}$$

Here, N_i represents the total number of peers connected to agent i, while N_{ia} denotes the number of agent i's peers who have adopted a heat pump at time t. As more peers adopt a heat pump, the influence of social networks becomes stronger, thereby increasing the probability that agent i will choose to install a heat pump at home.

3.7.5. Adoption decision

At time t, a potential adopter will decide to install a heat pump if the sum of the weighted partial utilities from the three factors, $U_{i,t}$, surpasses the adoption threshold θ_i, and the upfront cost remains within 50 % of the household's annual disposable income. This condition can be represented as:

$$U_{i,t} > \theta_i \text{ and } AC_{HP,i,t} \leq 0.5 \cdot Income_i \tag{7}$$

The threshold is shaped by each agent's willingness to adopt new technology. Some agents are early adopters, installing the technology when few others have done so, while others prefer to wait until a larger portion of the population has adopted it. Lower threshold values correspond to early adopters of heat pumps, whereas higher thresholds indicate those who adopt later, known as laggards [34]. We have included a detailed justification for defining agents' adoption propensity and value distribution, as well as for setting the income threshold at 0.5, in Appendix B.

Household income plays a significant role in the adoption of energy-efficient and renewable technologies, as higher-income households are more likely to invest in these systems due to the substantial upfront and installation costs, which can be a major barrier for lower-income households [19]. To account for the influence of household disposable income on heat pump adoption decisions, we define upfront costs exceeding 50 % of a household's annual disposal income as unaffordable. We set the threshold at 50 % for two reasons. First, it reflects the empirical context under study: the baseline upfront cost of £16,500 (including installation) represents about half of the average annual disposable income midpoint of UK households (£32,349), yet national adoption rates remain below 1 % [42]. Second, we adopt 50 % as a conservative upper bound on willingness to pay, consistent with evidence that high capital costs are the primary barrier to low-carbon heat adoption [7]. Consequently, an agent will decide to adopt a heat pump if the utility of adoption exceeds their heterogeneous willingness-to-pay threshold, and the upfront cost remains within 50 % of the household's annual disposable income.

3.8. Calibration, validation, and sensitivity analysis

To calibrate the model parameters, we used historical heat pump sales data for the UK from the Microgeneration Certification Scheme [42]. Because the UK dataset (2009–2024) is relatively short, we complemented it with Sweden's long-term adoption data covering 1993–2022 [45], following the comparative approach of Meles and Ryan [19]. The model assumes that the UK's heat pump diffusion trajectory follows a similar pattern to Sweden's more mature market. The model sets initial values of utility weights (economic 0.38, psychological 0.27, and social interaction 0.35) same to Meles and Ryan [19]. Calibration was performed using AnyLogic's OptQuest optimization engine. which systematically adjusted the three utility weights including economic, psychological, and social under the constraint that their sum equals one. The objective function minimized the root mean square error (RMSE) between the simulated adoption rates and observed UK data (2021–2024), while also aligning the long-term diffusion trend with the Swedish benchmark. The optimal weights identified (0.44 for economic, 0.27 for psychological, and 0.29 for social utility) yielded model trajectories that closely matched both datasets. This hybrid empirical–optimization calibration ensured that behavioural parameters were statistically grounded and that the model reproduced realistic adoption dynamics. Fig. 2 illustrates the calibration and validation process.

We run a single simulation over 30 time steps, where each step represents one year, based on the calibrated model. The simulation results from time steps 0 to 30 correspond to the cumulative number of adopters in the UK from 2021 to 2050, with the initial number of adopters derived from the survey representing the total by the end of 2021. To ensure statistical stability and reliability of the results, each simulation scenario was replicated 30 times, which represents a standard practice for balancing stochastic variability and computational feasibility. This approach follows the guidance of Macal and North [52] and Railsback and Grimm [53], who emphasise that multiple replications are essential to capture inherent stochasticity, even under identical model parameters and initial conditions. The output is collected and analysed using AnyLogic 8.9.3.

Table 3 presents the parameters used in both the baseline scenario and the sensitivity analysis. Since the data encompasses both ground source and air source heat pumps, we use midpoint values for key attributes of heat pumps in all of the scenarios: upfront cost (£17,500), bill savings (40 %), and lifespan (20 years). The baseline scenario incorporates the UK government's home grant of £7500 for heat pumps. To evaluate its impact on heat pump adoptions, we analyse scenarios where the grant is removed entirely (£0) or its amount varied at £5000, £9500 and £11,500. Additionally, we assess the sensitivity of the baseline scenario results to electricity price change. In the sensitivity analysis experiments, all other parameters are held constant at their baseline values, except for the variable of interest, which is modified individually.

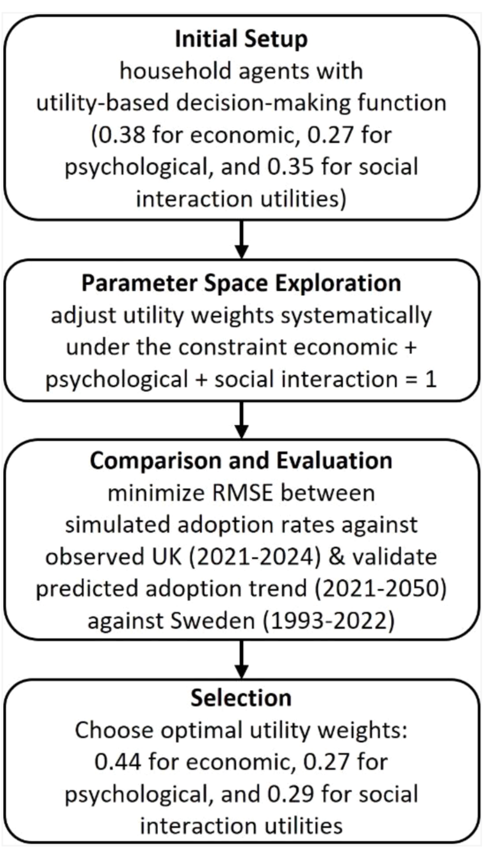

Fig. 2. The model calibration and validation progress.

Table 3
Parameter values for the baseline, policy and practical scenarios.

Variables	Baseline	Sensitivity Analysis
Grant amounts	£7500	£0, £5000, £9500, £11,500
%Δ in electricity price	0 %	−20 %, −10 %, +10 %, +20 %
Average weights for partial utilities:		
Economic utility	0.44	
Psychological utility	0.27	
Social utility	0.29	

Table 3 presents the model parameters that are applied in the baseline simulation and sensitivity scenarios, including grant levels, electricity price variations, and calibrated utility weightings.

4. Results

Section 4 presents and discusses both empirical findings from survey and historical datasets and model predictions generated through the agent-based simulations. The empirical data from the 2021 UK Public Attitudes Tracker [41] and historical heat pump sales [42] represent the current situation and serve as the baseline for model calibration. The simulated results represent projected adoption trajectories from 2025 to 2050 under different policy and market scenarios.

Specifically, Section 4.1 presents the baseline simulation predicting future heat pump uptake under 2021 policy conditions (a £7500 grant and constant electricity prices). Section 4.2 reports empirical logistic regression results on household socio-demographic and psychological factors influencing adoption. Sections 4.3 and 4.4 explore model-based policy scenarios, testing how variations in grant levels and electricity prices, respectively, affect projected adoption outcomes.

4.1. Predicting adoption among sample households and calibration to UK households

This subsection presents the simulation results on predicted cumulative adoptions of heat pumps among the 3706 sample households (base scenario) and the corresponding up-scaling of these results to the 28,119,000 UK households. Fig. 3 illustrates the average cumulative adoptions of heat pumps among sample and UK households across 30 simulated time steps, representing the years 2021 to 2050. To account for stochastic variation inherent in agent-based modelling, primarily due to random initialisation of household attributes and social network formation, we performed 30 independent simulation runs using the same parameter settings. The results from these runs were averaged to reduce the influence of random noise and improve the robustness of predictions. At the final time step (2050), the simulation, as indicated by the blue dotted line, predicts that 1141 of the 3706 sample households will adopt heat pumps, with a standard deviation of 12 across the 30 runs. These results were then proportionally up-scaled to the UK household population. As shown by the orange dotted line, the model estimates that approximately 8657,000 UK households—about 30.8 % of the total—will adopt heat pumps by 2050 under 2021 policy conditions (a £7500 grant and constant electricity prices), which assumes no additional policy interventions or incentives.

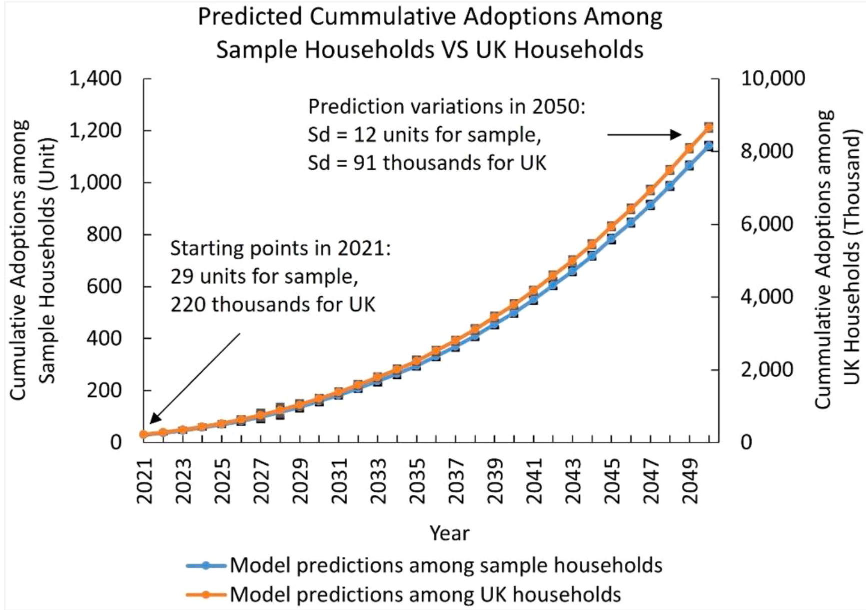

Fig. 3. Cumulative heat pump adoptions among sample households and the UK households.

4.2. Impacts of consumer socio-demographics and psychological factors

This subsection presents empirical analysis derived from national household survey data, not simulation outputs. Logistic regression was applied to identify key socio-demographic and psychological factors associated with the intention to adopt heat pumps. The statistically significant variables (in Table 4) were subsequently incorporated as parameters in the psychological utility component of the model and to inform agent-level characteristics. Specifically, the regression coefficients derived here are applied to estimate the probability that a household intends to replace its existing heating system, which in turn influences the agent's psychological utility score within the ABM. The empirical results indicate that households living in detached, semi-detached, or terraced homes are more inclined to adopt a heat pump compared to those living in flats. Similarly, homeowners—whether outright or with a mortgage—are significantly more likely to consider adoption than renters. Females are found to be less likely to adopt heat pumps than males, and individuals aged over 25 show greater adoption intent than those aged 16–24.

Table 4 presents the logistic regression results showing socio-demographic and psychological predictors of household intention to replace existing heating systems, informing the psychological utility component of the model. Significant levels are denoted by *(0.1), ** (0.05) and ***(<0.01). Observations: 3706.

In terms of psychological motivations, the empirical results show that households primarily motivated by minimising environmental impact are less likely to adopt than those focused on reducing heating costs. Additionally, households that report paying little or no attention to their heat usage—either due to lack of control or disinterest—are less inclined to adopt a heat pump than those motivated by maintaining comfort. These behavioural insights provide critical empirical grounding for the ABM's psychological and economic decision components. These empirically derived associations were used to construct the logistic function embedded in the agent-based model, thereby allowing agent decisions to reflect observed patterns in real-world adoption intent.

4.3. Policy scenario analysis: impact of grant variations

This subsection presents model-based simulations testing the sensitivity of household adoption to different grant levels. The empirical baseline reflects the UK Boiler Upgrade Scheme, which provides a £7500 grant [6]. The simulations vary grant values from £5000 to £11,500 in £2000 increments. The scenario of no grant (£0) is also considered. Fig. 4 presents simulated cumulative adoption trajectories under each scenario. The starting point (220 thousand adoptions in 2021) represents observed cumulative installations in 2021 as reported by MCS [42].

Based on the model predictions, the current £7500 grant increases the percentage of heat pump adopters to 30.8 % in 2050, equating to approximately 8657,000 households, compared to 3.5 % without any grant. This indicates that a grant covering 42.9 % of the upfront cost boosts the average cumulative number of adopters in 2050 by 27.3 % relative to the no-grant scenario. We also examine the effects of different grant levels, increasing from £5000 to £11,500 in step of £2000. A grant of £5000 reduces the average number of heat pump adopters in 2050 to 6601,000, compared to 8657,000 with the current £7500 grant. Conversely, grant amounts of £9500 and £11,500 increase the number of adopters in 2050 to approximately 39.7 % and 54.0 % of UK households (around 11,176,000 and 15,197,000 heat pumps), respectively, compared to 30.8 % with the £7500 grant.

4.4. Policy scenario analysis: impact of electricity price variations

Since heat pumps depend on electricity, this section presents simulation results assessing the influence of electricity price fluctuations relative to 2021 levels (the empirical baseline). Fig. 5 begins with 220 thousand observed cumulative installations in 2021 [42] and then shows modelled adoption trajectories under ±10 % and ±20 % electricity price scenarios. The model predicts that a 20 % reduction in electricity prices increases adoption by 12.2 percentage points (3.43 million additional installations) by 2050 relative to the baseline scenario. Conversely, the simulation results indicate price increases slow the adoption rate. Thus, it can be concluded that lower electricity prices would significantly increase the average cumulative percentage of heat pump adopters by 2050.

5. Discussions and policy implications

This study applies an ABM approach, underpinned by logistic regression analysis and utility theory, to explore the multifactorial dynamics of residential heat pump adoption in the UK from 2021 to 2050. By integrating economic, psychological, and social factors into

Table 4
Probability estimations of adopting a heat pump.

Variable type	Variable and variable category	Coefficient (Standard Deviation)
Psychological and behavioural variables	Main reason for paying a lot attention on heat usage (reference: cost):	
	To minimise the environmental impact of the heat used	-1.878*** (.279)
	Main reason for paying no attention on heat usage (reference: comfort):	
	I don't feel I can control the amount of heat used	-.900* (.480)
	I'm just not interested in the amount of heat used	-.854* (.501)
Socio-demographic variables	Accommodation type (reference: flat):	
	Detached	.664*** (.188)
	Semi-detached	.426** (.168)
	Terraced	.355** (.170)
	Tenure (reference: rent it):	
	Own outright	3.589*** (.158)
	Own with a mortgage or loan	3.969*** (.182)
	Part own and part rent	2.081*** (.410)
	Live here rent free	.895*** (.262)
	Gender (reference: male):	
	Female	-.384*** (.117)
	Age (reference: between 16 and 24 years old):	
	65 years old and above	1.231*** (.246)
	Between 45 and 64 years old	1.169*** (.222)
	Between 25 and 44 years old	1.058*** (.223)
	Constant	-.396 (.436)
	-2Log-likelihood	2096.441

Table 4 presents the logistic regression results showing socio-demographic and psychological predictors of household intention to replace existing heating systems, informing the psychological utility component of the model. Significant levels are denoted by *(0.1), **(0.05) and ***(<0.01). Observations: 3,706.

household agents' decision-making processes, and calibrating the model with national survey data and historical adoption trends, the simulation provides a robust representation of potential adoption pathways under varying policy and market conditions.

In the baseline scenario, where current (as of 2024) government subsidies and energy price levels are maintained, the model predicts that approximately 8.7 million UK households (30.8 %) could adopt heat pumps by 2050. However, the results reveal a high degree of sensitivity to both financial incentives and electricity price trends. Increasing the current £7500 grant to £11,500 could raise adoption to over 15 million households (54 % of households). In comparison, a 20 % reduction in electricity prices alone could boost adoption by a further 12.2 percentage points, resulting in a total adoption rate of approximately 43.0 % (equivalent to around 12.1 million households). These findings underline the pivotal role that economic levers, both direct subsidies and operational cost reductions, play in driving consumer transitions to low-carbon heating technologies. This finding is consistent with those of

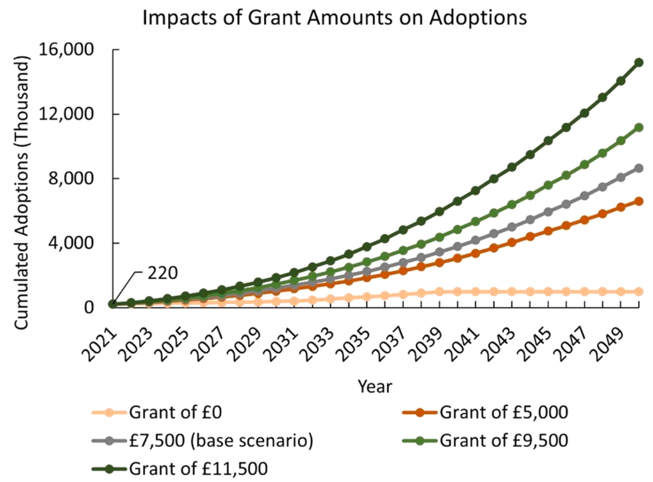

Fig. 4. Impacts of grant amounts on heat pump adoptions.

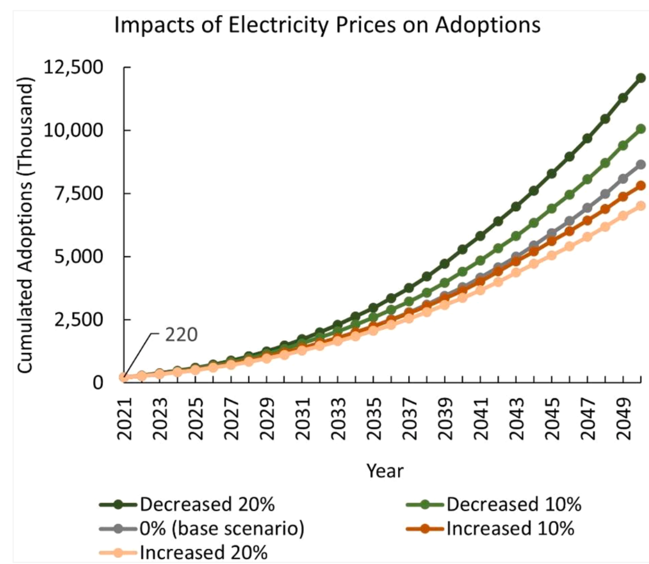

Fig. 5. Impact of electricity prices on heat pump adoptions.

Brodnicke et al. [24], van der Kam et al. [27], Derkenbaeva et al. [25], Nava-Guerrero et al. [30,21], Felten et al. [22] and Busch et al. [26], who similarly demonstrate the strong effect of policy portfolios like subsidies and cost reductions on adoption.

Beyond financial considerations, psychological and social dimensions are shown to be essential. Consumers who express stronger pro-environmental attitudes, greater control over heat usage, and motivation to save on heating bills are more likely to adopt heat pumps. Moreover, peer effects and social networks exert a meaningful influence, demonstrating that visibility of early adopters and community-based encouragement can accelerate diffusion. These behavioural insights align with previous findings of Meles and Ryan [19], Nava-Guerrero et al. [30,21] and Bale et al. [9], which suggest that a purely economic framing of policy may be insufficient to achieve widespread behavioural change. Our results on peer and social influence are also consistent with Sachs et al. [18] and Snape et al. [20], which find that adoption likelihood increases when peers have already installed heat pumps.

Six policy implications can be drawn from the research findings:

Expand and Tailor Financial Incentives: Increasing the Boiler Upgrade Scheme grant beyond £7500, particularly up to £9500–£11,500, could significantly increase adoption. In parallel, expanding eligibility to lower-income households through additional interest-free loans or tiered subsidies could enhance equitable access. The recommendation to expand the Boiler Upgrade Scheme grant is directly grounded in our finding that increasing grants from £7500 to £11,500 could raise adoption from 30.8 % to 54 % of households (from approximately 8657,000 to 15,197,000 adoptions) by 2050 (Fig. 4).

Reduce Operational Costs via Energy Pricing Reform: Lowering electricity tariffs for heat pump users, potentially through time-of-use pricing or green electricity discounts, could enhance the long-term cost-competitiveness of heat pumps and make them more attractive relative to fossil fuel systems. The suggestion to lower tariffs for heat pump users is supported by our result that a 20 % reduction in electricity prices boosts adoption by an additional 12.2 percentage points (3429,000 heat pumps in Fig. 5) by 2050.

Promote Social Norms and Community Initiatives: Public awareness campaigns should leverage social influence by showcasing early adopters and facilitating neighbourhood-scale transitions. Community heat pump trials, endorsements by trusted local figures, and social comparison tools (e.g., "compare your energy savings") can boost visibility and perceived legitimacy. The emphasis on peer influence derives from our social interaction utility modelling, which shows a positive weight in adoption decision.

Address Psychological Barriers: Educational efforts should focus on correcting misconceptions about the ease and reliability of heat pump installation and use. Demonstrating tangible co-benefits such as comfort, safety, and control can help shift attitudes and perceived behavioural control, especially among hesitant groups. This recommendation is drawn from our logistic regression analysis, which showed that negative attitudes (e.g., disinterest in heat usage) significantly reduce adoption intent.

Targeted Support for Renters and Flat Dwellers: Since adoption is lower among those in rented accommodation or flats, targeted interventions such as landlord incentives, building-wide retrofits, and regulations mandating low-carbon systems in multi-family housing are needed to prevent a "retrofit divide". Our finding that adoption likelihood is lower in rented accommodation or flats (Table 3) supports policies targeting landlords and multi-unit buildings.

Incorporate Behavioural Insights into Future Modelling: As the policy landscape and consumer attitudes evolve, future ABM efforts should incorporate dynamic adaptation of consumer preferences and more granular modelling of regional and housing-type variations.

In sum, achieving the UK's net-zero targets will require a comprehensive policy mix that goes beyond economic subsidies to include behavioural interventions, electricity market reform, and community engagement strategies. Agent-based modelling, by capturing the complex interplay between economic conditions, individual psychology, and social influence, offers a valuable tool for designing and evaluating such interventions.

Our research has made several contributions. Methodologically, the integration of logistic regression with ABM provides an empirically grounded weighting of economic, psychological, and social utilities. This hybrid approach advances existing ABM applications by combining statistical inference with behavioural simulation, thereby enhancing robustness and realism. Empirically, our long-term simulation (2021–2050), calibrated with both UK and Swedish adoption data, provides new insights into the trajectory of UK heat pump adoption under different policy scenarios. Our findings confirm prior evidence on the importance of financial incentives and social influence, while adding psychological attitudes (stronger pro-environmental attitudes, greater control over heat usage, and motivation to save on heating bills) as adoption drivers. Theoretically, this work explicitly connect the model to the Theory of Planned Behaviour, Diffusion of Innovations, and Utility Theory, showing how these frameworks guided the construction of adoption progress, utility weights, and agent heterogeneity. In turn, our results inform TPB by empirically demonstrating the relative weighting of economic versus psychological and social drivers, highlighting that financial incentives alone are insufficient to trigger mass adoption and quantifying the interplay of TPB constructs in long-term technology diffusion.

This research has several limitations. Firstly, it is confined to the context of the UK, which may limit the generalisability of the findings to other regions. Cross-national studies across different countries and cultural backgrounds are recommended to assess the broader applicability of the results. Secondly, variations in how TPB is operationalised in ABMs, such as differences in model architecture, equation structure, factor representation, and underlying data distributions, can affect outcomes. This limitation in a broader context of TPB-based ABM has been evidenced by Muelder and Filatova [54]. Future studies should therefore explore alternative approaches to assess robustness. Thirdly, more extensive stochastic exploration (e.g., sensitivity analysis of social network variations using Latin Hypercube Sampling or Monte Carlo experiments) could provide additional insights into model uncertainty. However, given computational constraints and the focus of this paper, we limited the stochastic analysis to the main adoption outcomes. Fourthly, key variables such as the discount rate, annual heating bills, and household socio-demographic and psychological characteristics are assumed to be static. System age and residential lifetime are not incorporated. Further studies are encouraged to incorporate more dynamic variables into the model to better reflect real-world complexities. Fifthly, other sources of uncertainty can substantially influence heat pump adoption, such as technology cost trajectories (e.g., declining installation costs with market maturity or economies of scale), and policy landscape uncertainty and future regulatory requirements (e.g., building standards, gas boiler phase-out timelines). Subsequent studies should incorporate multiple interacting uncertainties to enhance the robustness of model-based policy insights. Lastly, our model assumption on direct proxies of survey respondents for household decision-maker agents may over-represent certain categories, especially younger respondents who may not yet be the primary decision-makers in their households. Although empirical calibrations of utility weights and adoption trends may reduce but cannot eliminate the bias. We recommend that future research should adjust survey-based ABM populations using household-level weighting schemes (e.g., linking microdata to household structure statistics).

6. Conclusion

This study develops a TPB-based agent-based model, integrated with logistic regression and utility function (incl. economic, psychological, and social interaction utilities), to explore residential heat pump adoption in the UK. By empirically calibrating utility weights using UK and Swedish adoption data, the model reproduces reliable diffusion dynamics and projects future adoption trajectories by 2050 under varying policy and market conditions. The results confirm that grant amounts and electricity price reductions are key drivers of adoption, while attitudes, perceived control, and social norms, which are core constructs of TPB, also strongly influence household decisions. Effective decarbonisation strategies should therefore combine financial support with behavioural interventions and social engagement initiatives. Beyond its empirical insights, this research advances TPB-informed ABM approaches, offering a robust framework for assessing policy efficacy and supporting the UK's transition toward low-carbon heating.

Data Statement

Supporting data is available to bona fide researchers, subject to registration, from the UK Data Service at http://doi.org/10.5255/UKDA-SN-9025-2.

CRediT authorship contribution statement

Wen Xu: Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Meysam Qadrdan:** Writing – review & editing, Supervision, Software, Resources, Project administration, Funding acquisition.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests Meysam Qadrdan reports financial support was provided by Engineering and Physical Sciences Research Council. If there are other authors, they 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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Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.sftr.2025.101601.

Data availability

The authors do not have permission to share data.

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