2025 European Conference on Computing in Construction
CIB W78 Conference on IT in Construction
Porto, Portugal
July 14-17, 2025

AN AGENT-BASED SIMULATION OF HOUSEHOLD HEATING ADOPTION: INTEGRATING BAYESIAN BELIEF UPDATING

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Abstract

This paper presents an agent-based model to simulate household decisions transitioning from gas-reliant heating. Households consider three options: installing a gas-free heat pump, adopting district, or doing nothing. The model integrates the Theory of Planned Behavior and Bayesian updating of household beliefs about technology performance, cost-effectiveness, and reliability. It also accommodates four decision-making styles—rational, satisficing, social, and conservative—that govern how households interpret information and manage risk. Results reveal how these styles, social influence, and belief updates drive adoption patterns and transition speed. Insights support targeted policies and interventions to accelerate the shift to sustainable heating technologies.

Introduction

Reducing dependence on natural gas for residential heating is critical to achieving climate targets and mitigating greenhouse gas emissions. Policymakers and stakeholders are interested in accelerating the uptake of cleaner technologies, such as heat pumps (HP), while also considering district heating (DH) systems, which may still rely partly on gas but also have the potential to be gas-free. However, households are not facing a binary decision; instead, they encounter multiple options, each with distinct cost, performance, risk, and infrastructural profiles (Koirala et al., 2016; Wolske et al., 2020). These heating technology choices occur within a complex socio-technical landscape where infrastructure availability, local policies, and community adoption patterns can significantly influence household decisions (Brown et al., 2019).

Existing research often simplifies household decision-making in energy transitions. Many models assume that households are economically rational actors with homogeneous preferences, complete information, and uniform decision criteria, focusing primarily on cost-benefit analysis or payback periods (Michelsen & Madlener, 2016). These approaches overlook the complexity and heterogeneity observed in real-world contexts, where uncertainty about technology attributes, diverse risk perceptions, and social influence are all at play (Kastner & Stern, 2015).

Real-world transitions to gas-free heating involve heterogeneous household behaviors unfolding under uncertainty. Households differ in their technical knowledge, trust in emerging technologies, sensitivity to social norms, and willingness to act under uncertain conditions. They must often learn about technology performance and reliability over time, relying on both personal experience and the observed successes or failures of others (Palm, 2018). Yet many existing models do not fully capture these adaptive learning processes or the rich behavioral diversity that characterizes consumer segments in energy markets. Furthermore, the interplay between learning processes and decision-making styles remains understudied, particularly in contexts where multiple competing technologies are available (Zhang & Vorobeychik, 2019).

To address this gap, this research integrates Bayesian belief updating and heterogeneous decision-making styles into an agent-based model (ABM) of household heating technology adoption. Bayesian updating allows households to refine their beliefs about technology attributes as they accumulate evidence from their own and neighbors' experiences (Gelman et al., 2013). Incorporating varied decision styles reflects empirical findings that households employ different heuristics, place varying emphasis on financial, environmental, or social factors, and react differently to uncertainty and peer influence (Kahneman, 2011; Wilson et al., 2015).

By modeling these processes, this paper aims to move beyond traditional rational-choice frameworks and capture more realistic patterns of technology adoption. This approach provides a richer understanding of how cleaner heating options diffuse under complex social dynamics and diverse household motivations. In doing so, it can offer policymakers insights into how tailored interventions, such as performance guarantees for cautious adopters or community demonstration projects to leverage social influence, might accelerate sustainable heating transitions.

Background and Related Work

Transitions Toward Gas-Free Heating

The shift from gas-based heating to cleaner systems is a pressing challenge in many European regions (European Commission. Joint Research Centre., 2020). Policy instruments, incentives, and regulations increasingly push households toward sustainable solutions. Understanding the complex decision environment, where multiple technologies coexist and evolve, is key to anticipating adoption barriers and identifying effective levers for policy intervention.

Theory of Planned Behavior in Energy Decisions

The Theory of Planned Behavior posits that attitudes, subjective norms, and perceived behavioral control shape intentions and behaviors (Ajzen, 1991). In heating technology adoption, these factors reflect how households evaluate attributes (attitude), respond to social networks and peer choices (subjective norm), and perceive their capability or resources to adopt (PBC) (Abrahamse & Steg, 2011; Zhou & Yang, 2016). Yet TPB-based models often assume that households have stable preferences and sufficient information. In reality, attitudes and perceived control evolve as households learn and gain confidence in their understanding of emerging technologies.

Bayesian Belief Updating

Bayesian updating offers a theoretical foundation for modeling how households incorporate new information and reduce uncertainty over time (Gelman et al., 2013; Rogers, 2010). For example, households uncertain about HP performance can update their beliefs after observing neighbors' successful installations. Similarly, studies show that learning-by-observation and accumulating evidence significantly impact decisions (Bandura, 1977; Palm, 2018). By representing beliefs with probability distributions and revising them based on incoming evidence, Bayesian updating captures the real-world processes of trial, observation, and adaptation.

For binary outcomes (e.g., success/failure), the Beta distribution is the conjugate prior for the Bernoulli likelihood. After observing an outcome $\boldsymbol{O} \in \{success, failure\}$:

$$\begin{aligned} &If\ \boldsymbol{O} = success: \alpha_{new} = \alpha_{old} + 1 \\ &If\ \boldsymbol{O} = failure: \beta_{new} = \beta_{old} + 1 \end{aligned} \tag{1}$$

This update is derived from Bayes' rule. Let θ be the unknown "quality" parameter of an attribute. Initially:

$$p(\theta) = \frac{\theta^{\alpha-1}(1-\theta)^{\beta-1}}{B(\alpha,\beta)} \tag{2}$$

where $B(\alpha,\beta)$ is the Beta function. After observing a success, the posterior becomes:

$$p(\theta|success) \propto \theta^{(\alpha+1)-1}(1-\theta)^{\beta-1} = Beta(\alpha+1,\beta) \tag{3}$$

Similarly, after a failure:

$$p(\theta|failure) \propto \theta^{\alpha-1}(1-\theta)^{(\beta+1)-1} = Beta(\alpha,\beta+1) \tag{4}$$

Iterating this process over multiple observations refines beliefs, making them more certain (narrower Beta distributions) as α and β increase.

Heterogeneous Decision-Making Styles

Empirical research in consumer segmentation and behavioral economics reveals that households vary widely in their decision-making approaches (Kahneman, 2011; Sütterlin et al., 2011). Rational households analyze data thoroughly and demand strong evidence before adopting. Satisficing households seek "good enough" solutions to reduce decision complexity (Simon, 1997). Social households rely heavily on peer experiences and recommendations, aligning with findings that social networks strongly influence technology uptake (Bollinger & Gillingham, 2012). Conservative households are risk-averse and hesitant to change, waiting for substantial proof before acting (Wilson et al., 2015)

Incorporating these distinct decision-making styles is essential for modeling realistic adoption dynamics. Understanding these different decision-making styles is also crucial for policy design, as interventions effective for rational decision-makers may fail to persuade those who rely more heavily on social cues or require extensive risk mitigation (Frederiks et al., 2015).

Model Description

This section describes the model's structure and the decision-making process households follow. Each household has three options: installing an air-source heat pump (gas-free), adopting district heating (potentially not fully gas-free, somewhat less clean, but cheaper), or doing nothing. This model evolves from the previous work (Mu et al., 2024), in which an agent-based framework for household heating technology was introduced. This model extends that baseline by incorporating additional behavioral factors, addressing the complexity of household decision processes.

Model Entities and Environment

The model consists of a set of households (agents) embedded in a social environment. The simulation proceeds in discrete time steps (years). Each step, households observe changes in technology performance, costs, and their neighbors' adoption patterns, then update their beliefs and potentially switch to a cleaner technology. Each agent has unique socioeconomic attributes (income, savings), preferences (environmental concern), and building characteristics (insulation level). Attributes of cost-effectiveness and efficiency concerns are integrated into each agent's utility calculation via the Net Present Value (NPV) and a performance evaluation function. Specifically, households assign varying weights to short-term costs, long-term energy savings, and efficiency gains, with parameter values drawn from open-source data (Table 2 in Mu et al., 2024).

NPV quantifies the long-term economic attractiveness of adopting a new heating system. The model calculates NPV as:

$$NPV(T) = \sum_{t=0}^{T_L - 1} \frac{B_t - C_t}{(1+r)^t} \tag{5}$$

Where T_L is the technology lifespan, B_t represents annual benefits, such as reduced energy bills or incentives. C_t includes upfront installation costs (usually C_0 at $t = 0$) and any maintenance costs. r is the discount rate.

Bayesian Belief Representation

Households hold beliefs about three key attributes for both HP and DH: Performance, the technology's ability to meet thermal needs effectively; Cost-Effectiveness, the long-term financial benefits or drawbacks; Reliability, how consistently and dependably the system provides heating over time.

These beliefs are represented using Beta distributions. As households gain information from their own experiences or by observing neighbors' outcomes, the Beta parameters would update. A positive observation (e.g., a neighbor's successful and cost-effective installation) increases α, while a negative outcome (such as poor performance or system reliability issues) increases β (Gelman et al., 2013). Over time, repeated Bayesian updates narrow these distributions and give households a more informed understanding of each technology's likely performance, costs, and reliability.

Integrating Beliefs into the Theory of Planned Behavior

For each technology option, compute three components: Attitude (A), represents households' beliefs about the technology's attributes; Subjective Norm (SN), reflects the influence of peers; Perceived Behavioral Control (PBC), captures how feasible households perceive the adoption to be.

These three are combined to form a utility-like score for each technology option. Households weigh these components differently, reflecting population heterogeneity.

Decision-Making Styles

While TPB provides the core evaluation framework, households differ in how they interpret and act on this information. Four decision-making styles is considered, each with a unique approach to information processing, thresholds for action, and responsiveness to uncertainty.

Table 1: Four Decision-Making styles.

Rational	Prioritize comprehensive analysis and robust evidence. Adopt only when the evidence strongly favors it.
Satisficing	Willing to adopt a suboptimal solution if it meets a certain acceptable standard.
Social	More likely to adopt whichever technology their community favors.
Conservative	Less swayed by early adopters and require consistently positive signals over time.

Decision-Making Process in Each Time Step

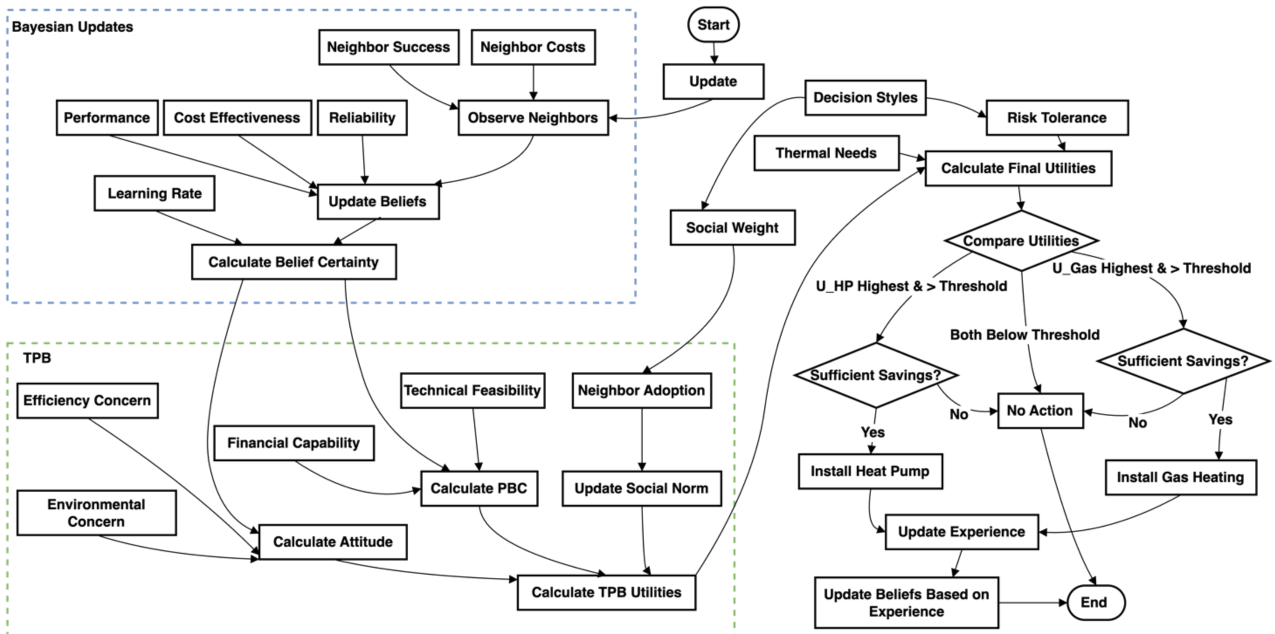


Figure 1: The decision-making process.

The steps are:

1. Bayesian Belief Updating:

Each household's belief about a given attribute is represented using a Beta distribution. To begin with relatively uninformed priors:

$$Belief(X) \sim Beta(\alpha_0, \beta_0) \tag{6}$$

where α_0 and β_0 are initial parameters, often set to modest values (in this model $\alpha_0 = 2$, $\beta_0 = 2$) to reflect limited initial knowledge.

When a household observes an outcome related to an attribute, it updates its belief distribution. Suppose a household observes a binary outcome $o \in \{0,1\}$, where $o = 1$ indicates a positive and $o = 0$ indicates a negative experience. This outcome occurs in two ways: households' direct experience or the observation of neighbors' experience.

The household adjusts the Beta distribution parameters α and β to incorporate this new information. Let α_{old} and β_{old} be the parameters before observing the outcome. After observing the outcome, the parameters are updated as follows:

$$\alpha_{new} = \alpha_{old} + o \cdot \Delta\alpha(o)$$
$$\beta_{new} = \beta_{old} + (1 - o) \cdot \Delta\beta(o) \tag{7}$$

$\Delta\alpha(o)$ and $\Delta\beta(o)$ represent increments to α and β that depend on the observed outcome o. When the outcome is positive ($o = 1$), $\Delta\alpha(1) > 0$ and $\Delta\beta(1) = 0$ increasing the "success" count. When the outcome is negative ($o = 0$), $\Delta\alpha(0) = 0$ and $\Delta\beta(0) > 0$, increasing the "failure" count.

To reach reality, the increments $\Delta\alpha(o)$ and $\Delta\beta(o)$ are not fixed in this model. They depend on learning rate (η), a parameter controlling how quickly beliefs change in response to new evidence, and the decision-making style. Different household styles adjust their beliefs with different sensitivity.

Thus, the detailed formula is:

$$\alpha_{new} = \alpha_{old} + o \cdot \eta \cdot I_s(style)$$
$$\beta_{new} = \beta_{old} + (1 - o) \cdot \eta \cdot I_f(style) \tag{8}$$

Here, I_s(style) and I_f(style) are style-specific multipliers. For instance, a conservative household might have smaller increments (lower I_s and I_f) to reflect its higher skepticism, whereas a social household might have higher increments, being more responsive to neighbors' experiences.

After the update, the household's belief about the technology attribute is:

$$Belief_{new}(X) \sim Beta(\alpha_{new}, \beta_{new}) \tag{9}$$

As more observations accumulate, the Beta distribution shifts, narrowing as α and β grow. When α significantly exceeds β, the household's belief leans strongly toward success. Conversely, if β outpaces α, the household becomes increasingly convinced of poor outcomes.

2. Calculate TPB Components and Combined into Utilities:

For each option (HP, DH), compute the utility for each technology:

$$U_t = \omega_A A_t + \omega_{SN} SN_t + \omega_{PBC} PBC_t \tag{10}$$

where ω_A, ω_{SN}, ω_{PBC} are weightings of the three components (Niamir et al., 2018).

3. Make the Choice Based on Decision-Making Style:

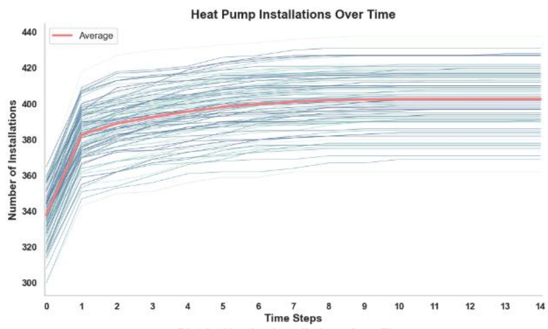
Adjust and interpret the utilities based on the household's style. If a household finds that the utility of HP or DH meets its style-specific criteria (threshold), it adopts that technology. Otherwise, it remains with the original system and awaits more information in future steps.

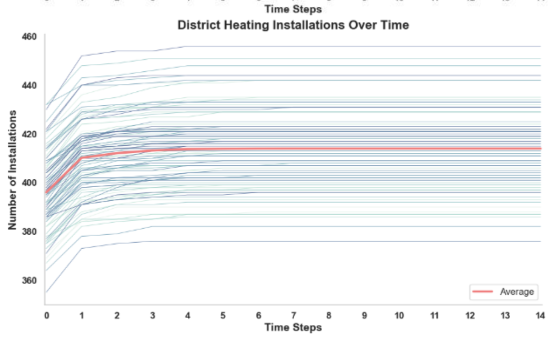
Simulation Setup and Implementation

The model initializes households with randomly assigned incomes, savings, and house characteristics based on open-source residential characteristic data in the Netherlands. Discount rates and CO2 emission factors are also incorporated (Mu et al., 2024).
The simulation runs for multiple time steps (15 years), updating energy costs, beliefs, and household states each year. The model tracks key outputs, such as the fraction of households adopting each technology, the evolution of belief certainty, and how these patterns vary by decision-making style. Data are collected at agent and model levels, facilitating analysis of aggregate outcomes and style-specific behaviors.

Results and Discussion

Results





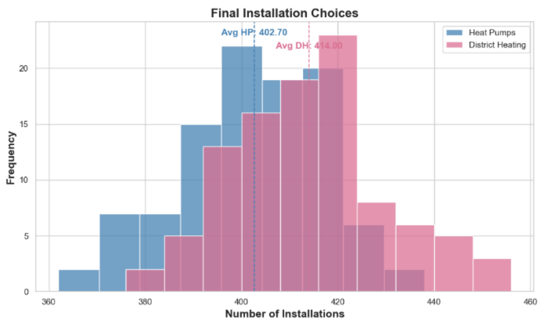


Figure 2: (a)(b) Installation numbers of each investment option; (c) Final Installation Histogram

The results are from multiple simulation runs of 1000 households.

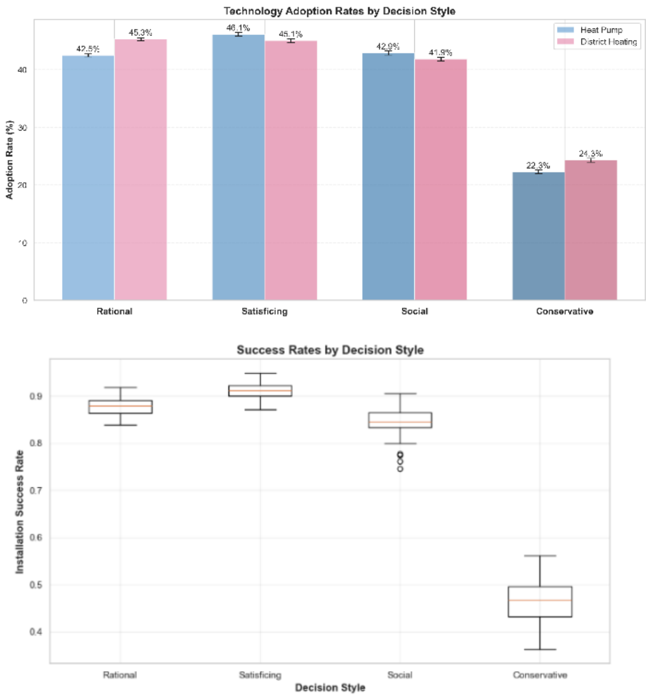


Figure 3: (a) Adoption Rates by Decision Styles; (b) Success Rates by Decision Styles

Figure 2(c) provides a distribution of final installation counts for HP and DH across all runs. On average, slightly more households opt for DH than HP, although both technologies gain substantial market shares in the long run. The histograms show that while outcomes vary from run to run, the bulk of final adoption levels cluster around these mean values, indicating a relatively stable equilibrium scenario where both HP and DH coexist as viable alternatives.

Figure 3(a) shows that households with rational or satisficing decision-making styles achieve comparatively high adoption rates for both technologies, often exceeding 40%. Conservative households remain less inclined to switch, showing significantly lower adoption levels.

Further insights come from installation success rates from Figure 3(b). Rational and satisficing households achieve high success rates, often exceeding 90%. Social households, while generally achieving high adoption levels, have slightly lower success rates, possibly due to their willingness to follow neighbors without ensuring optimal conditions. Conservative households display distinctly lower success rates, hovering around 50–60%. This may be counterintuitive, as one might expect a cautious strategy to lead to better outcomes. Instead, waiting too long or insisting on perfect information could mean missing early opportunities for incentives or accumulating experience, leading to less favorable conditions by the time they adopt.

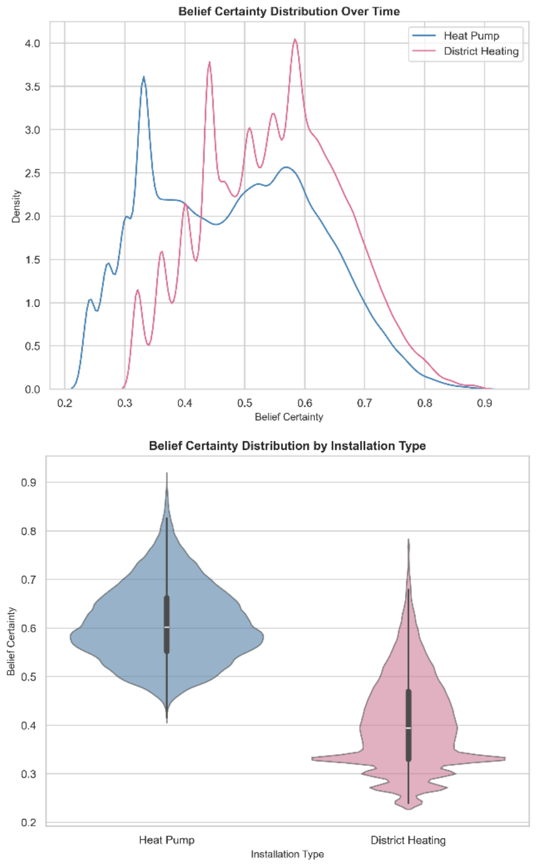


Figure 4: (a)(b) Bayesian Analysis of Belief Certainty

Figure 4 shows the distribution of belief certainty, an important driver in how households perceive and evaluate the technologies over time. Figure 4(a) shows the distribution of belief certainty evolves as households accumulate evidence, with both HP and DH belief certainties gradually shifting toward higher values. Initially, belief certainty distributions are broad and skewed, reflecting uncertainty. Over time, as Bayesian updating incorporates observed successes or failures, these distributions narrow and shift upward.

Figure 4(b) (a violin plot) compares the final distributions of belief certainty among households. On average, DH adopters tend to have slightly higher and more narrowly distributed belief certainties. This suggests that DH, potentially seen as a "middle-ground" or more consistently understood option, leads to more uniformly high confidence among its adopters.

Discussion

These results highlight the interplay of behavioral heterogeneity, information dynamics, and social influence in a gas-free heating transition. The final equilibrium, where both HP and DH remain attractive, implies that promoting a portfolio of cleaner technologies may yield robust market outcomes. Compared to the earlier model (Mu et al., 2024), which assumed relatively fixed agent beliefs, these results show slower but more realistic adoption waves, with some agents deferring decisions until they accumulate enough "success" evidence.

From a policy perspective, understanding how different decision-making styles respond to incentives and information can guide the design of tailored interventions.

For rational and satisficing households, ensuring transparent performance data, stable subsidies, and accessible cost-benefit information can encourage earlier adoption. Social households benefit from strategies that increase visibility and credibility of early adopters—community endorsements or demonstration projects can prompt rapid cascades of uptake. Conservative households, however, pose a tougher challenge. Policymakers might employ long-term performance warranties, risk-sharing arrangements, or enhanced policy signals that reduce perceived risks and uncertainties, gradually eroding the barriers that keep these households from embracing cleaner technologies.

Lastly, fostering environmental awareness and trust in cleaner solutions may indirectly boost adoption rates by strengthening positive attitudes and reducing uncertainty over time.

Conclusion

This study presents an ABM integrating TPB, Bayesian belief updating, and heterogeneous decision-making styles to examine household heating technology adoption. In contrast to the more static approach developed previously, the new modeling approach highlights adaptive learning: households refine their views on cost-effectiveness, reliability, and performance as they or their neighbors gain experience. The results emphasize that how households process information, respond to social cues, and handle uncertainty shapes the pace and scale of technology transitions. Policymakers can leverage these insights to design tailored interventions—such as educational campaigns to increase performance transparency for rational households, targeted demonstrations for conservative adopters, or leveraging community leaders for social adopters.

Future work will incorporate a wider range of societal parameters and expand the model's calibration with empirical surveys or real-world adoption data. A deeper exploration of network structures and targeted policy interventions is also planned.

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