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Social and Behavioral Modeling of Community Adoption of Hybrid Renewable Energy Systems

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Abstract
Hybrid renewable energy systems support decarbonization at the community scale, yet adoption remains uneven and slower than projected by techno-economic models. This paper develops an integrative socio-technical synthesis of the social, behavioral, and institutional drivers of community adoption and links them to formal modeling approaches. A systematic review of peer-reviewed studies published between 2010 and 2025 is conducted using a PRISMA-guided protocol. The analysis identifies subjective norms, perceived behavioral control, trust, and governance equity as primary determinants of adoption, while financial incentives act as necessary but insufficient conditions for sustained uptake. The study shows that models grounded only in cost optimization fail to reproduce observed diffusion patterns, whereas approaches that embed behavioral theory capture heterogeneous decision processes and social influence effects. Agent-based modeling emerges as the most suitable framework for representing these dynamics, especially when integrated with constructs from the Theory of Planned Behavior, Technology Acceptance Model, and Unified Theory of Acceptance and Use of Technology. Evidence also indicates growing relevance of behavioral economics and digital infrastructures, including peer-to-peer energy trading, in shaping prosumer participation. Geographic imbalance in the literature and limited use of adaptive, data-driven modeling remain key gaps. The paper advances a unified framework that connects behavioral theory, governance design, and computational modeling to improve explanatory power and policy relevance. This framework supports the design of interventions that align incentives, strengthen social acceptance, and enable equitable energy transitions.

Keywords
hybrid renewable energy systems · community adoption · social acceptance · agent-based modeling · behavioral economics · energy governance · socio-technical systems

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1. Introduction

1.1 Background and Rationale

Hybrid renewable energy systems integrate multiple generation and storage technologies to provide reliable and low-carbon electricity at the community scale. Despite clear technical progress and cost reductions, adoption remains slower than projected. This gap reflects limits in dominant modeling approaches, which treat adoption as a cost-driven and fully rational process. Empirical evidence shows that such assumptions fail to explain observed adoption patterns across different social contexts [1][2].

Behavioral and social factors play a central role in shaping adoption decisions. Perceived social pressure, individual sense of control, and trust in institutions influence whether households and communities engage with new energy systems [3]. These factors operate within local social structures, where norms, peer effects, and visibility of early adopters shape collective behavior. In many cases, projects with strong economic value still face resistance due to weak social acceptance or lack of participatory governance [4].

Current research reveals a structural mismatch between techno-economic predictions and real adoption trajectories. Models that exclude social interaction and behavioral diversity fail to capture key dynamics such as delayed uptake, clustering of adoption, and resistance within specific groups. As a result, policy recommendations based only on economic incentives often underperform when implemented in practice.

A systematic integration of behavioral theory with energy system modeling is required to address this limitation. Linking social determinants with formal modeling approaches provides a stronger basis for explaining adoption patterns and designing effective interventions.

1.2 Objectives

This paper has four objectives. First, it identifies the main social and behavioral determinants influencing community adoption of hybrid renewable energy systems. Second, it evaluates modeling approaches used to represent adoption dynamics, with focus on agent-based modeling and behavioral frameworks. Third, it analyzes how policy instruments and governance structures interact with behavioral responses. Fourth, it develops an integrated socio-technical framework to guide future research and policy design.

2. Literature Review: Social and Behavioral Factors in Community Adoption of HRES

2.1 Theoretical Frameworks

2.1.1 Technology Acceptance Model (TAM)

The Technology Acceptance Model explains adoption through perceived usefulness and perceived ease of use. In hybrid renewable energy systems, usefulness reflects expected savings, reliability, and environmental gains, while ease of use relates to system operation and accessibility. Evidence shows these factors influence early-stage acceptance but do not fully capture collective or sustained adoption patterns [5]. Extensions of TAM within broader socio-psychological frameworks improve explanatory strength by incorporating social influence and contextual constraints.

2.1.2 Theory of Planned Behavior (TPB)

The Theory of Planned Behavior links behavior to attitudes, subjective norms, and perceived behavioral control. Empirical studies show these constructs jointly explain a large proportion of variance in renewable energy adoption intentions [3]. Subjective norms reflect peer influence and community expectations, while perceived control captures access to financial, technical, and institutional resources. This framework demonstrates that positive attitudes alone do not lead to adoption without supportive social and structural conditions.

2.1.3 Unified Theory of Acceptance and Use of Technology (UTAUT)

UTAUT integrates multiple behavioral models and includes performance expectancy, effort expectancy, social influence, and facilitating conditions. Its strength lies in capturing the role of infrastructure and institutional support. Evidence shows that facilitating conditions such as financing access, technical support, and regulatory clarity directly affect adoption decisions and moderate behavioral intentions [5]. This makes UTAUT suitable for policy-oriented analysis.

2.1.4 Diffusion of Innovations (DoI)

Diffusion of Innovations frames adoption as a process driven by communication and perceived attributes of the technology. Relative advantage, compatibility, complexity, trialability, and observability determine diffusion speed. Studies in renewable energy show that compatibility with local practices and visibility of early adopters strongly influence uptake [6]. This framework shifts focus from individual decision-making to network effects and information flow.

Framework	Core Constructs	Strength in HRES Context	Key Limitation	Reference
TAM	Usefulness, Ease of Use	Explains early acceptance	Weak on social dynamics	[5]
TPB	Attitudes, Norms, Control	Strong predictive ability	Limited system-level dynamics	[3]
UTAUT	Expectancy, Social Influence, Conditions	Integrates policy and infrastructure	Higher complexity	[5]
DoI	Innovation attributes, communication	Captures diffusion patterns	Less focus on individual cognition	[6]

Table 1 Comparison of Core Behavioral Frameworks in HRES Adoption

2.2 Social and Behavioral Determinants

2.2.1 Social Norms and Community Influence

Social norms shape collective adoption behavior. Peer influence, local champions, and shared identity affect how communities evaluate new energy systems. Projects based on participatory governance and collective ownership show higher adoption rates and stronger long-term engagement [4]. Evidence also shows that combined personal and collective motivations increase participation when communities perceive both individual and shared benefits [1].

2.2.2 Economic and Policy Incentives

Financial incentives such as subsidies, tax credits, and feed-in tariffs reduce adoption barriers. Scenario analyses show that well-designed incentives shorten payback periods and improve financial viability [7]. Yet, their impact weakens over time if not supported by trust, transparency, and community involvement [8].

2.2.3 Behavioral Economics and Heuristics

Adoption decisions are shaped by cognitive biases. Loss aversion, present bias, and preference for existing options lead individuals to undervalue long-term benefits. Empirical studies show that behavioral interventions such as simplified financing and social comparison feedback increase adoption rates [9][10]. These findings challenge assumptions of rational decision-making in traditional energy models.

2.2.4 Equity and Justice in Energy Transitions

Equity in cost and benefit distribution affects acceptance and long-term participation. Projects perceived as unfair or imposed without consultation face resistance. Inclusive governance and transparent decision-making increase trust and stability [4]. Equity functions as both a social and institutional determinant of adoption.

Determinant	Mechanism	Observed Effect	References
Social norms	Peer influence, visibility	Accelerates diffusion	[1], [4]
Financial incentives	Cost reduction	Strong initial uptake	[7]
Behavioral biases	Decision heuristics	Delays adoption	[9], [10]
Governance equity	Trust, fairness	Sustains long-term adoption	[4]
Facilitating conditions	Infrastructure, policy	Enables adoption	[5], [8]

Table 2 Key Determinants and Their Effects on HRES Adoption

3. Modeling Approaches for Community Adoption of HRES

3.1 Agent-Based Modeling (ABM)

Agent-based modeling represents systems as collections of interacting agents such as households, prosumers, and local authorities. Each agent follows decision rules and interacts within a defined social and spatial environment. This structure allows the model to capture heterogeneity, peer effects, and feedback loops, which are central to community energy adoption. Systematic reviews show that ABM reproduces observed diffusion patterns more accurately than aggregate models, especially when social interaction and network structure are included [11].

ABM is suited for exploring policy scenarios. It allows simulation of interventions such as subsidies, awareness campaigns, and governance changes under controlled conditions. Studies demonstrate that ABM captures non-linear adoption dynamics, including threshold effects and clustering, which are not represented in traditional optimization models [12]. These features make it a strong tool for evaluating community-scale energy transitions.

Recent developments extend ABM with adaptive learning. Reinforcement learning techniques allow agents to update strategies based on past outcomes, which improves representation of real decision processes. Applications in local electricity markets show that such models capture dynamic trading behavior and evolving participation patterns within communities [13]. Other work applies ABM to optimize energy sharing and pricing strategies, linking behavioral dynamics with system efficiency [14].

3.2 Hybrid Modeling: Integration with Behavioral Theories

The predictive strength of ABM increases when agent decision rules are grounded in behavioral theory. Frameworks such as TPB, TAM, and UTAUT provide structured variables that define how agents evaluate decisions. For example, subjective norms can be represented through network influence, while perceived usefulness can be linked to expected cost savings.

Empirical studies show that hybrid models generate diffusion patterns that align with real-world observations more closely than models based only on economic assumptions [11]. These models capture variation in adoption across social groups and explain delayed or uneven uptake. Integration also allows direct testing of policy interventions by modifying behavioral parameters, such as increasing perceived control through financial support or strengthening norms through information campaigns.

Approach	Key Features	Strengths	Limitations	Reference
Optimization models	Cost minimization, aggregate behavior	High computational efficiency	Ignores social dynamics	[11]
ABM	Heterogeneous agents, interactions	Captures diffusion and behavior	Higher data and calibration needs	[11], [12]
ABM + Behavioral Theory	Behavioral decision rules	High predictive realism	Model complexity	[11]

ABM + Reinforcement Learning	Adaptive agents	Captures dynamic learning	Limited empirical validation	[13]

Table 3 Comparison of Modeling Approaches

3.3 Empirical Applications and Validation

Applications across different regions confirm the importance of integrating social and behavioral factors into models. Studies of renewable energy communities show that models including governance structure, incentives, and social influence produce adoption trajectories consistent with observed data [7][8]. In contrast, models excluding these factors tend to overestimate adoption speed and fail to capture resistance or stagnation phases.

Empirical validation remains a challenge due to limited longitudinal data. Most studies rely on short-term observations or scenario-based assumptions. Despite this, convergence across case studies supports the conclusion that incorporating behavioral and social variables improves model reliability and policy relevance.

Capability	Optimization Models	ABM	Hybrid ABM
Social interaction	No	Yes	Yes
Behavioral heterogeneity	No	Yes	Yes
Policy simulation	Limited	Strong	Strong
Diffusion dynamics	Weak	Strong	Very strong
Real-world alignment	Low	Moderate	High

Table 4 Modeling Capabilities and Policy Relevance

4. Data and Methodology

4.1 Systematic Review Protocol

A structured review protocol was applied to ensure transparency and reproducibility. The study followed PRISMA guidelines for identification, screening, and inclusion of relevant literature. Searches were conducted across Scopus, Web of Science, ScienceDirect, SSRN, and publisher databases including MDPI. The search string combined three domains: social acceptance, hybrid or community renewable energy systems, and behavioral or modeling approaches. Boolean operators were applied as follows: (“community adoption” OR “social acceptance”) AND (“hybrid renewable energy” OR “renewable energy community”) AND (“agent-based model” OR “behavioral economics” OR “theory of planned behavior” OR “technology acceptance model”).

The search covered publications from January 2010 to June 2025. Inclusion criteria required peer-reviewed status, explicit focus on community or collective adoption, and direct treatment of social, behavioral, or modeling dimensions. Review articles were included to capture theoretical development. Exclusion criteria removed purely technical system design studies, non-community-scale analyses, and articles lacking empirical or modeling relevance.

Criterion Type	Description
Inclusion	Peer-reviewed articles, 2010–2025, focus on community adoption, inclusion of behavioral or modeling aspects
Inclusion	Empirical studies, modeling studies, systematic reviews
Exclusion	Purely technical optimization studies without social variables
Exclusion	Studies focused only on individual technology adoption without community context
Exclusion	Non-English publications and non-accessible full texts

Table 5 Inclusion and Exclusion Criteria

4.2 Data Extraction and Synthesis

A standardized extraction framework was used to ensure consistency. Each study was coded across four dimensions: theoretical framework, behavioral constructs, modeling approach, and policy variables. Behavioral constructs included social norms, perceived control, incentives, trust, and governance structure. Modeling attributes included agent types, interaction rules, calibration methods, and validation approach.

The synthesis followed a thematic aggregation process. First, determinants were grouped into social, economic, behavioral, and institutional categories. Second, modeling approaches were classified based on structure and level of behavioral integration. Third, cross-study comparison was conducted to identify consistent patterns and divergences. This approach allowed linking empirical findings with modeling strategies.

Category	Variables Extracted
Theoretical framework	TPB, TAM, UTAUT, DoI
Behavioral factors	Norms, control, trust, incentives
Modeling approach	ABM, hybrid models, optimization
Policy variables	Subsidies, governance, regulation
Outcomes	Adoption rate, intention, diffusion pattern

Table 6 Data Extraction Structure

4.3 Quality Assessment

Quality assessment focused on methodological rigor and relevance. Studies were evaluated based on clarity of theoretical framework, transparency of modeling assumptions, and presence of validation or empirical grounding. Modeling studies without clear parameter justification or validation were weighted lower in synthesis. Empirical studies with weak sampling or unclear measurement of behavioral constructs were also treated cautiously.

4.4 Limitations

The review is limited to published academic literature, which introduces risk of publication bias. Studies reporting positive or significant findings are more likely to be included in indexed databases. Geographic representation is uneven, with stronger coverage in Europe and North America. In addition, differences in measurement methods across studies limit direct comparability of results.

Results and Discussion

5.1 Key Findings

5.1.1 Behavioral Determinants

Across the reviewed literature, subjective norms and perceived behavioral control emerge as the most consistent predictors of adoption. These factors influence both intention and actual participation, especially in community settings where decisions are socially embedded. Evidence shows that individuals are more likely to adopt when they observe peers adopting and when they perceive sufficient capability and support to engage with the system [3][1].

Financial incentives increase initial interest and reduce entry barriers, yet their effect weakens over time without reinforcement from social and institutional factors. Studies indicate that incentives alone do not sustain participation unless combined with trust-building measures and community engagement strategies [7][8]. Behavioral biases further affect outcomes. Loss aversion and preference for existing arrangements delay adoption even when long-term benefits are clear. Interventions such as simplified financing and peer comparison mechanisms increase participation rates and reduce resistance [9][10].

5.1.2 Policy and Governance

Governance structure plays a central role in shaping adoption outcomes. Projects with inclusive decision-making processes and transparent benefit-sharing mechanisms achieve higher levels of trust and participation. Community ownership models and participatory planning approaches support long-term engagement and reduce conflict [4][1].

Digital platforms for energy management and trading introduce new forms of interaction. Evidence from recent modeling studies shows that decentralized trading systems increase engagement by giving participants more control over energy use and revenue flows [13]. In contrast, top-down policy designs that exclude community input often face resistance and lower sustained adoption [8].

5.1.3 Modeling Insights

Modeling results confirm that approaches incorporating social and behavioral variables produce more realistic adoption patterns. Agent-based models capture heterogeneity, peer influence, and feedback loops, which are essential for representing diffusion processes. When combined with behavioral frameworks, these models reproduce observed S-shaped adoption curves and account for delays and clustering effects [11][12].

In contrast, models based only on economic optimization predict rapid and uniform adoption, which does not match empirical evidence. The inclusion of adaptive learning mechanisms further improves model performance by allowing agents to adjust decisions over time in response to experience and environmental changes [13].

Dimension	Main Result	Implication
Behavioral factors	Norms and perceived control dominate	Social strategies required alongside incentives
Economic incentives	Strong initial effect	Limited long-term impact without social support
Governance	Inclusive structures increase trust	Participation improves sustainability
Modeling	Hybrid ABM performs best	Integration of behavior improves prediction

Table 7 Summary of Key Findings

5.2 Comparative Analysis

Approach	Predictive Accuracy	Policy Relevance	Ability to Capture Social Dynamics	References
TAM	Moderate	Low	Low	[5]
TPB	High	Moderate	Moderate	[3]
UTAUT	High	High	Moderate	[5]
DoI	Moderate	Moderate	High	[6]
ABM	High	High	High	[11][12]
Hybrid ABM	Very High	Very High	Very High	[11][13]

Table 8 Comparative Performance of Frameworks and Models

The comparison shows a clear progression. Behavioral theories improve prediction at the individual level, while agent-based approaches extend this capability to system-level dynamics. Hybrid models combine both strengths and provide the most consistent alignment with empirical observations.

5.3 Gaps and Future Research

Four main gaps emerge from the analysis. First, geographic coverage remains uneven, with limited representation from developing regions. This restricts generalizability of findings and limits understanding of context-specific drivers. Second, few studies integrate adaptive or data-driven methods such as machine learning to refine behavioral parameters over time. Third, the role of digital technologies in shaping social norms and participation remains underexplored. Fourth, longitudinal data is limited, which constrains validation of long-term adoption dynamics.

Addressing these gaps requires interdisciplinary approaches that combine empirical research, behavioral theory, and advanced modeling. Expanding data collection across diverse regions and integrating adaptive modeling techniques will improve both explanatory depth and policy relevance.

6. Policy and Practical Implications

6.1 For Policymakers

Effective policy design requires alignment between financial mechanisms and social dynamics. Evidence shows that subsidies and financial incentives increase early adoption but do not sustain participation without trust, transparency, and community engagement [7][8]. Policies must therefore combine economic support with measures that strengthen social acceptance. These include structured awareness programs, support for local champions, and mechanisms that increase visibility of successful projects.

Regulatory frameworks that enable community ownership and decentralized energy exchange improve participation and long-term stability. Systems that allow peer-to-peer trading and shared ownership structures increase perceived control and strengthen engagement [13]. In parallel, policy design must address equity. Unequal distribution of costs and benefits leads to resistance and project failure. Mandatory equity assessments and transparent allocation rules reduce conflict and improve legitimacy [4].

6.2 For Practitioners

Project implementation strategies must prioritize participation from early stages. Community involvement in planning, design, and governance increases acceptance and reduces delays. Pilot projects and demonstration sites improve observability, which accelerates diffusion through peer influence [6]. Clear communication of economic and social benefits improves trust and reduces uncertainty.

Practitioners must also address behavioral barriers directly. Simplified financing structures, staged investment options, and feedback systems that show comparative performance across users increase participation rates [9][10]. Inclusion of diverse community groups in decision-making processes improves both adoption speed and long-term stability.

6.3 For Researchers

Future research must move beyond isolated modeling or behavioral analysis. Integration of behavioral frameworks within agent-based models provides a stronger foundation for explaining adoption dynamics. Empirical validation requires longitudinal data and broader geographic coverage, especially in underrepresented regions.

There is also a need to incorporate adaptive methods. Machine learning techniques can refine agent behavior based on observed data, which improves model accuracy over time. Research on digital infrastructures such as decentralized trading platforms remains limited and requires systematic investigation, especially in relation to their influence on trust and social norms [13].

Stakeholder	Action	Expected Outcome
Policymakers	Combine incentives with engagement strategies	Sustained adoption
Policymakers	Enable community ownership models	Higher participation
Practitioners	Use pilot and demonstration projects	Faster diffusion
Practitioners	Simplify financing and feedback systems	Reduced behavioral barriers

Researchers	Integrate behavioral theory with ABM	Improved predictive accuracy
Researchers	Expand data collection across regions	Higher model validity

Table 9 Alignment of Actions with Outcomes

7. Conclusion

Community adoption of hybrid renewable energy systems depends on social and behavioral conditions as much as on technical and economic factors. Evidence shows that subjective norms, perceived behavioral control, trust, and governance structures shape both adoption intention and long-term participation. Financial incentives reduce initial barriers but do not sustain engagement without alignment with social dynamics and institutional design [3][7].

This study provides an integrated synthesis linking behavioral theory, governance, and modeling approaches. It shows that models based only on economic optimization fail to reproduce observed adoption patterns. In contrast, agent-based models that incorporate behavioral constructs capture heterogeneous decision processes, social influence, and diffusion dynamics more accurately [11][12]. Hybrid approaches that combine behavioral theory with simulation methods offer the highest explanatory and predictive strength.

The analysis also identifies key gaps. Research remains concentrated in specific regions, which limits generalizability. Adaptive modeling techniques remain underused, and the role of digital infrastructures in shaping behavior requires further investigation. Addressing these gaps will improve both empirical understanding and model performance.

A unified socio-technical framework is required to guide future work. This framework must connect behavioral determinants, policy design, and system modeling in a consistent structure. Such integration enables more accurate prediction of adoption patterns and supports the design of interventions that align economic incentives, social acceptance, and institutional trust.

8. Declaration

8.1 Availability of data and material

Not applicable.

8.2 Funding

Not applicable.

8.3 Acknowledgements

Not applicable.

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