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Understanding and Enhancing Rural Adoption of Distributed Rooftop Photovoltaic Systems: An Integrated Analysis of Behavioral Drivers and Policy Interventions

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Abstract: The transition to low-carbon energy systems is a global imperative, with distributed renewable energy playing a pivotal role. In China, county-wide distributed rooftop photovoltaic (DRPV) systems represent a significant opportunity for rural energy transformation and carbon reduction. However, widespread adoption among rural residents faces substantial social and behavioral barriers. This study employs a novel mixed-methods approach to dissect the complex factors influencing rural households' participation in DRPV projects. First, we harness large-scale, multi-platform online textual data (2014–2024) to perform dynamic topic modeling using the BERTopic framework, identifying evolving public perceptions related to cost, risk, technology, and policy. These emergent themes are then integrated with the established Unified Theory of Acceptance and Use of Technology (UTAUT) to construct a comprehensive theoretical model. The model is empirically tested using structural equation modeling (SEM) on survey data collected from 828 rural residents in Jiangsu Province. Results indicate that facilitating conditions—primarily shaped by technical perception and government-led safeguards—exert the strongest direct influence on participation behavior ($\beta = 0.582$, $p < 0.001$). Behavioral intention, while significant, shows a weaker effect ($\beta = 0.347$, $p < 0.001$). Social influence emerges as the most potent driver of intention ($\beta = 0.424$, $p < 0.001$), surpassing performance expectancy ($\beta = 0.253$, $p < 0.001$) and effort expectancy ($\beta = 0.301$, $p < 0.01$). Notably, rural residents demonstrate a dual valuation of economic returns and environmental co-benefits. The study concludes that effective DRPV promotion requires a multi-pronged strategy: enhancing institutional support and technical assistance to improve facilitating conditions; leveraging community networks and on-site consultation to amplify social influence; and implementing targeted financial instruments to mitigate cost sensitivity. These findings offer evidence-based policy insights for accelerating rural PV diffusion in China and similar contexts globally.

Keywords: *Distributed rooftop photovoltaic (DRPV); Rural energy transition; Technology acceptance; UTAUT; Topic modeling; Structural equation modeling; Social influence; Policy design*

1. Introduction

The existential threat of climate change, underscored by the Paris Agreement's goals to limit global warming to well below 2°C and pursue efforts towards 1.5°C, has catalyzed an international consensus on the urgent need for a low-carbon energy transition (Li et al., 2024; Lu et al., 2024). This transition is fundamentally predicated on the large-scale displacement of fossil fuels by renewable

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energy sources (Rabbi, 2025; Li et al., 2022). However, the conventional, centralized model of renewable energy deployment often encounters limitations related to land use, grid infrastructure, and social acceptance, particularly for technologies like solar and wind which have a lower energy density (Pramadya & Kim, 2024; Tro-Cabrera et al., 2025). In this context, distributed energy systems have gained prominence as a complementary pathway, offering advantages in flexibility, localization, and the efficient use of existing infrastructure, such as building rooftops (Liu et al., 2023; Zhang et al., 2020).

Rooftop photovoltaic (PV) systems epitomize this distributed paradigm. By converting underutilized rooftop spaces into decentralized power generation assets, they offer a promising solution for enhancing energy security, reducing transmission losses, and empowering prosumers (Ghaleb & Asif, 2022; Shen et al., 2021). The global technical potential is vast, with estimates suggesting suitable rooftop area capable of generating 8.3 petawatt-hours annually (Gernaat et al., 2020). China, as the world's largest energy consumer and carbon emitter, has identified distributed PV, particularly in rural areas, as a strategic pillar for achieving its "dual carbon" goals (carbon peak and neutrality) and advancing rural revitalization (Yang et al., 2023; Zhao & Xie, 2019). The National Energy Administration's initiative for county-wide DRPV pilot projects underscores this strategic focus.

Despite strong policy impetus and significant potential, the grassroots implementation of DRPV in rural China has encountered formidable challenges. Resistance or reluctance from rural residents, stemming from a complex interplay of economic, social, and psychological factors, has emerged as a critical bottleneck (Wang et al., 2023; Wu et al., 2023). Existing literature highlights issues such as high perceived costs, concerns over system reliability and contract pitfalls, limited technical literacy, and a general risk aversion that favors immediate gains over long-term investments (Yang et al., 2023; Aklin et al., 2018). Understanding the nuanced drivers and barriers shaping rural residents' adoption decisions is therefore essential for designing effective, human-centric promotion policies.

Traditional approaches to studying technology acceptance, such as surveys and interviews based on theoretical models like the Theory of Planned Behavior (TPB) or the Technology Acceptance Model (TAM), have provided valuable insights (Ajzen, 1991; Davis, 1985). The Unified Theory of Acceptance and Use of Technology (UTAUT), which synthesizes several of these models, has proven particularly robust in various contexts, including renewable energy adoption (Venkatesh et al., 2003; He et al., 2020; Jain et al., 2022). However, these methods often rely on a priori theoretical constructs and may miss emergent, context-specific factors that shape public perception in real-time.

The digital age offers a complementary lens. Social media and online platforms have become primary arenas for public discourse, where perceptions, concerns, and narratives about technologies like DRPV are organically formed and evolve (Jeong et al., 2023). Computational text analysis and topic modeling present powerful tools to mine this unstructured data, capturing the zeitgeist of public opinion and identifying salient themes that may not be fully captured in pre-designed survey instruments.

This study aims to bridge this methodological gap and address the identified research need by pursuing three key objectives: (1) To dynamically map the evolution of public discourse and identify key perceptual dimensions (e.g., cost, risk, policy) related to rural DRPV in China through advanced topic modeling of multi-source online textual data; (2) To integrate these contextually derived perceptual factors with the established UTAUT framework to develop a comprehensive theoretical model of rural DRPV adoption; and (3) To empirically validate this integrated model using field survey data and structural equation modeling, thereby elucidating the relative importance and interplay of different drivers—including social influence, facilitating conditions, and cost perceptions—on participation intention and behavior.

By adopting this mixed-methods approach, the study contributes to both theory and practice. Theoretically, it demonstrates the value of augmenting classic acceptance models with data-driven, emergent factors, enhancing their explanatory power in complex socio-technical transitions. Practically, it provides policymakers and project developers with granular, evidence-based insights into the levers that most effectively influence rural households, informing the design of targeted, culturally resonant, and institutionally robust strategies to accelerate the rural energy revolution.

The remainder of this paper is organized as follows. Section 2 reviews the relevant literature on renewable energy acceptance, rural energy transitions, and the application of UTAUT. Section 3 details the mixed-methods methodology, encompassing online data analysis (BERTopic) and survey-based SEM. Section 4 presents the development of the theoretical framework by merging topic modeling results with UTAUT. Section 5 reports the empirical results, including descriptive statistics, measurement model validation, and SEM path analysis. Section 6 discusses the findings in relation to existing literature and derives key implications. Finally, Section 7 concludes with a summary of the study's contributions, policy recommendations, and directions for future research.

2. Literature Review

2.1 Public Acceptance of Energy Projects: From NIMBY to Multifaceted Engagement

Public acceptance is a well-established critical success factor for energy infrastructure projects. Early research, particularly on fossil fuel and nuclear facilities, often framed local opposition through the lens of the "Not-In-My-Backyard" (NIMBY) syndrome, attributing resistance to selfish parochialism (Hermansson, 2007; Pol et al., 2006). This perspective has been increasingly challenged as reductionist. Contemporary studies recognize that public attitudes are shaped by a complex matrix of factors including perceived risks and benefits (economic, environmental, health), trust in developers and regulators, procedural justice (fairness in decision-making), and place-based attachments (Carlisle et al., 2016; Wüstenhagen et al., 2007).

For renewable energy projects, which are often more visible and spatially diffuse than conventional energy infrastructure, the acceptance landscape is equally if not more complex. While their environmental benefits are a general positive factor, local opposition can arise from concerns over visual impact, noise (for wind), land use change, and perceived threats to property values or community character (Enserink et al., 2022; Olve et al., 2025). Scognamiglio (2016) argues that the aesthetic integration of PV systems into the landscape is a crucial and often underestimated determinant of social acceptance. Studies like that of Rodriguez-Segura et al. (2023) further emphasize that acceptance is not monolithic but varies by technology, location, and specific project characteristics.

2.2 The Rural Energy Transition Context

Rural areas, with their abundant land and renewable resources (solar, biomass, micro-hydro), are indispensable arenas for the global energy transition (Huang et al., 2020). However, they present unique challenges. These include infrastructural gaps, financial constraints, lower average technical literacy, and stronger reliance on social and kinship networks for information and decision-making (Qureshi et al., 2017; Yadav et al., 2020). An "equity paradox" has been noted, where low-income communities may bear disproportionate burdens or receive fewer benefits from renewable deployments (Outka, 2020).

Research on solar PV adoption in rural settings globally identifies recurring barriers: high upfront costs, lack of access to affordable financing, concerns about technology performance and maintenance, information asymmetry, and mistrust of vendors or government schemes (Aklin et al., 2018; Devereux et al., 2021). In the Chinese context, studies by Wang et al. (2023) and Wu et al. (2023) confirm similar patterns, highlighting the strong influence of peer behavior ("authoritative persuasion") and a pronounced sensitivity to risk and immediate economic returns among rural households.

2.3 Theoretical Frameworks for Technology Acceptance: The UTAUT Model

To systematically analyze the psychological drivers of technology adoption, researchers have employed various behavioral theories. Venkatesh et al. (2003) conducted a seminal synthesis of eight prominent models, including the Theory of Reasoned Action, TAM, and TPB, to develop the Unified Theory of Acceptance and Use of Technology (UTAUT). The core of UTAUT posits that four key constructs directly determine usage intention and behavior: Performance Expectancy (the degree to which using a system will provide benefits), Effort Expectancy (the degree of ease associated with using the system), Social Influence (the degree to which important others believe one should use the system), and Facilitating Conditions (the degree to which organizational and technical infrastructure exists to support use).

UTAUT's parsimony and strong explanatory power have led to its widespread application and extension in diverse fields, including green technology adoption. For instance, Jain et al. (2022) extended UTAUT with environmental concerns and perceived risk to study electric vehicle adoption in India. He et al. (2020) successfully applied it to understand farmers' willingness to pay for crop straw energy utilization in rural China. Agozie et al. (2023) further incorporated psychological empowerment to explain renewable technology recommendation behaviors. These applications demonstrate UTAUT's robustness and adaptability as a foundational framework for studying renewable energy acceptance.

2.4 The Role of Online Discourse and Mixed Methods

While surveys grounded in theories like UTAUT are powerful, they are constrained by their static and researcher-defined nature. Concurrently, the explosion of user-generated content on social media provides a rich, real-time repository of public sentiment and framing (Hong et al., 2022; Jeong et al., 2023). Advanced natural language processing (NLP) techniques, such as topic modeling, allow researchers to inductively identify the salient themes and concerns within this discourse. The integration of such data-driven insights with traditional survey-based theory testing represents a powerful mixed-methods approach. It allows for theory to be informed by emergent, ground-level discourse, leading to more contextually valid and comprehensive models. However, as identified in the introduction, few studies on rural DRPV have systematically employed such an integrated methodology to build and test their theoretical models.

This study seeks to address this gap by dynamically mining online discourse to inform the extension of UTAUT, then rigorously testing the resulting integrated model with empirical field data. This approach aims to provide a more holistic and nuanced understanding of the drivers behind rural DRPV adoption in China.

3. Methodology

This study employs a sequential mixed-methods design, structured in two primary phases: (1) a qualitative-computational phase involving the collection and thematic analysis of online textual data to identify key perceptual factors, and (2) a quantitative phase involving survey design, data collection, and structural equation modeling to validate an integrated theoretical framework. This design ensures that the model is both grounded in emergent public discourse and rigorously tested against empirical behavioral data.

3.1 Phase 1: Online Textual Data Analysis

3.1.1 Data Collection and Preprocessing
To capture a comprehensive view of public discourse on rural DRPV, data was gathered from multiple Chinese social media platforms known for diverse user demographics and content formats: TikTok (short videos), Bilibili (long-form videos), Zhihu (Q&A forum), and Weibo (microblogging). Using a set of keywords including "county-wide distributed rooftop PV" and "residential distributed PV systems," a total of 370,000 text entries (including video titles, descriptions, comments, article texts, and answers) were collected for the period from January 2014 to February 2024. This longitudinal span allows for the analysis of discourse evolution.

The raw text data underwent a multi-step preprocessing pipeline. First, a custom stop-word lexicon was developed to filter out platform-specific noise and high-frequency irrelevant terms (e.g., common internet slang). Next, the NLPir Semantic Analysis Toolkit was employed for word segmentation, a crucial step for processing Chinese text, which lacks natural word delimiters. The output was a cleaned and tokenized corpus ready for thematic analysis.

3.1.2 Thematic Modeling with BERTopic
For thematic analysis, we utilized BERTopic, a state-of-the-art topic modeling technique proposed by Grootendorst (2022). Unlike traditional methods like Latent Dirichlet Allocation (LDA), BERTopic leverages pre-trained transformer-based language models (like BERT) to capture deeper semantic meaning, resulting in more coherent and contextually relevant topics.

The BERTopic process involves three key stages:

1. Document Embedding: Each document in the corpus is converted into a dense vector representation using the Sentence Transformer model, capturing its semantic meaning.
2. Dimensionality Reduction and Clustering: The high-dimensional embeddings are reduced to a lower dimension (e.g., 5) using Uniform Manifold Approximation and Projection (UMAP) to preserve local and global structure. The reduced embeddings are then clustered using HDBSCAN (Hierarchical Density-Based Spatial Clustering), a robust algorithm that identifies clusters of varying density and treats outliers as noise.
3. Topic Representation: For each cluster, keywords are extracted using a class-based variant of TF-IDF (C-TF-IDF). This method calculates term importance within a specific cluster relative to all clusters, effectively highlighting words that are distinctive to a topic. The formula is:

$$W_{t,c} = TF_{t,c} \times \log\left(1 + \frac{A}{DF_t}\right)$$

where Wt,cWt,c is the weight of term tt in class cc, TFt,cTFt,c is its frequency in class cc, AA is the average number of terms per class, and DFtDFt is the number of classes containing term tt.

The parameters for the BERTopic model were carefully tuned (see Table 1 in the original text), including setting the language to simplified Chinese and the number of top words per topic to 10. Topic quality was validated using Word2Vec semantic similarity checks, confirming a high average relevance

(>0.8) between texts and their assigned topic keywords.

TABLE 1. BERTopic Model Parameters

Parameter	**Value**
Language	Simplified Chinese
Embedding Model	SentenceTransformer
Dimensionality Reduction	UMAP (reduced to ~5 dimensions)
Clustering Algorithm	HDBSCAN
Top Words per Topic	10
Validation	Word2Vec semantic similarity (>0.8)

3.1.3 Topic Evolution Analysis
To understand how public discourse shifted over time, the dataset was partitioned by year. Topics were generated for each annual corpus. Cosine similarity between the C-TF-IDF keyword vectors of topics in adjacent years was calculated. A Sankey diagram was then constructed to visualize the flow, convergence, divergence, and disappearance of topics from 2014 to 2024, revealing key inflection points in public perception.

3.2 Phase 2: Survey and Model Validation

3.2.1 Integration of Findings and Theoretical Framework Development
The key perceptual themes (e.g., cost, risk, technology, policy) identified from the 2023 online data—deemed most representative of current discourse—were analyzed by a 15-member expert panel. The panel mapped these themes onto the constructs of the UTAUT model as potential antecedent or shaping factors. This integration formed the initial theoretical model (M1), where perceptual factors were hypothesized to influence the core UTAUT constructs (Performance Expectancy, Effort Expectancy, Social Influence, Facilitating Conditions), which in turn drive Behavioral Intention and Use Behavior.

3.2.2 Questionnaire Design and Pilot Study
Measurement items for the core UTAUT constructs were adapted from established scales in relevant literature (e.g., Jain et al., 2022; He et al., 2020; Sarker et al., 2025). Items for the new perceptual factors (cost, technology, policy) were developed based on the keywords and text examples from the topic modeling. All items used a 5-point Likert scale (1 = strongly disagree, 5 = strongly agree).

A pilot study was conducted in rural areas of Wuxi and Xuzhou, Jiangsu Province. 100 questionnaires were distributed, and 10 in-depth interviews were held. The pilot revealed that respondents conflated "risk perception" with "cost perception," leading to poor discriminant validity in preliminary factor analysis. Consequently, risk perception was conceptually and operationally merged into the broader cost perception construct, resulting in the revised theoretical model M2.

3.2.3 Sampling and Data Collection
The main survey targeted rural residents in Jiangsu Province, a region with active DRPV pilot projects. A multistage stratified random sampling method was employed:

1. Selection of representative counties within the province.
2. Stratification of villages within counties (e.g., traditional agricultural, suburban).
3. Random selection of administrative villages.
4. Targeting of young and middle-aged residents (primary decision-makers) with basic education to ensure comprehension of the survey.

A total of 862 questionnaires were distributed, with 828 valid responses retained after removing incomplete or inconsistent entries, yielding a high validity rate of 96%.

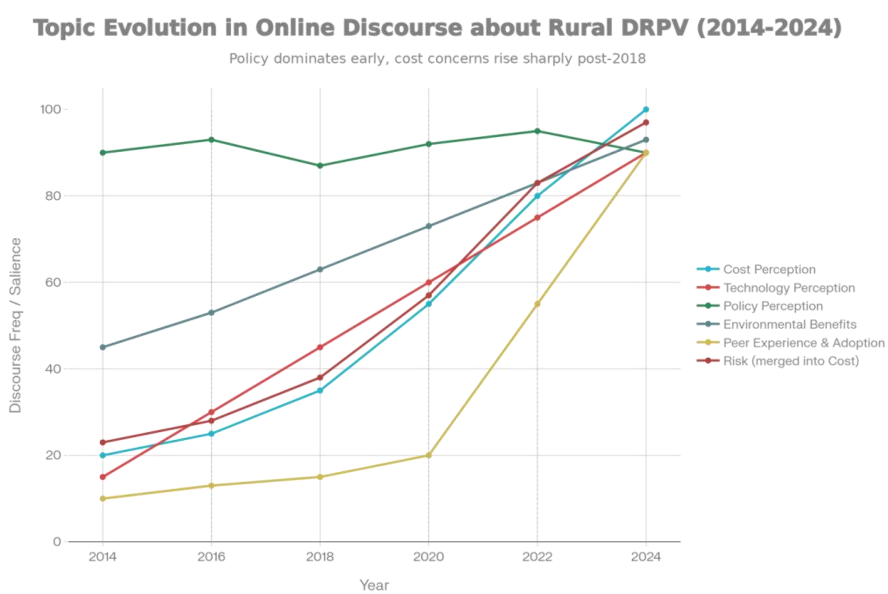
3.2.4 Data Analysis: Structural Equation Modeling (SEM)

SEM was chosen for its ability to model complex relationships among latent (unobserved) constructs and test the entire theoretical model simultaneously. The analysis proceeded in two stages using SPSS 26.0 and AMOS software.

1. Measurement Model Assessment: Confirmatory Factor Analysis (CFA) was conducted to evaluate reliability and validity.
    - Reliability: Assessed using Cronbach's alpha ($\alpha > 0.7$ acceptable) and Composite Reliability (CR > 0.7 ideal).
    - Validity: Convergent validity was assessed using Average Variance Extracted (AVE > 0.5 acceptable). Discriminant validity was checked by ensuring the square root of AVE for each construct was greater than its correlations with other constructs.
2. Structural Model Assessment: The hypothesized causal paths were tested.
    - Model Fit: The overall fit of the structural model was evaluated using multiple indices: χ^2/df (<3 good), GFI (>0.85), CFI (>0.9), TLI (>0.9), RMSEA (<0.08), and RMR (<0.05).
    - Path Analysis: Standardized path coefficients (β) and their significance levels (p-values) were examined to test the research hypotheses. Modification indices were consulted to improve model fit if necessary, leading to the final model M3.

4. Theoretical Framework and Hypothesis Development

The integrated theoretical framework guiding this study is presented in Figure 2 (original text). It posits that rural residents' participation in DRPV projects (Use Behavior) is directly determined by their Behavioral Intention and the Facilitating Conditions present. Behavioral Intention, in turn, is shaped by Performance Expectancy, Effort Expectancy, and Social Influence. Crucially, these core UTAUT constructs are not isolated; they are hypothesized to be significantly influenced by antecedent perceptual factors derived from the online discourse analysis.



- Cost Perception (CP): This encompasses awareness of upfront installation costs, ongoing operational expenses, and perceived financial risks (e.g., contract fraud, poor returns). High cost perception is expected to negatively impact both the perceived benefits (Performance Expectancy) and the perceived ease (Effort Expectancy) of adoption.
  - H1a: Cost Perception has a significant negative effect on Performance Expectancy.
  - H1b: Cost Perception has a significant negative effect on Effort Expectancy.
- Technology Perception (TP): This relates to understanding of system components, installation processes, maintenance needs, and grid compatibility. A positive perception of technology reliability and simplicity is expected to strengthen the belief that adequate support structures (Facilitating Conditions) exist or can be accessed.
  - H2: Technology Perception has a significant positive effect on Facilitating Conditions.
- Policy Perception (PP): This involves awareness and evaluation of government incentives (subsidies, feed-in tariffs), pilot programs, and regulatory support. Positive policy perception is expected to create a normative environment where adoption is encouraged and endorsed by authorities and peers, thereby amplifying Social Influence.
  - H3: Policy Perception has a significant positive effect on Social Influence.

The core UTAUT relationships are also hypothesized:

- H4: Performance Expectancy has a significant positive effect on Behavioral Intention.
- H5: Effort Expectancy has a significant positive effect on Behavioral Intention.
- H6: Social Influence has a significant positive effect on Behavioral Intention.
- H7: Facilitating Conditions have a significant positive effect on Use Behavior.
- H8: Behavioral Intention has a significant positive effect on Use Behavior.

5. Results

5.1 Descriptive Statistics of Respondents

The demographic profile of the 828 valid respondents is summarized in Table 4 (original text). The sample was relatively balanced in gender (52% male, 48% female). The age distribution was concentrated in the 21-40 bracket (87.5%), confirming the targeting of the primary household decision-making cohort. Reflecting the significant investment required for DRPV, the sample skewed towards higher-income and more educated households: 73.9% reported annual household income above CNY 80,000, and 74.6% held a bachelor's degree. This profile suggests the sample represents the "early majority" or potential early adopters within the rural population, whose perceptions and decisions are critical for initial project diffusion.

TABLE 2. Sample Demographics

Variable	Category	Percentage (%)
Gender	Male	52.0
	Female	48.0
Age	21–40 years	87.5
	Others	12.5 (not specified)
Income	Above CNY 80,000	73.9
	Below CNY 80,000	26.1

Variable	Category	Percentage (%)
Education	Bachelor's degree	74.6
	Others	25.4
Valid samples	N = 828	—

5.2 Measurement Model Evaluation

The results of the reliability and validity tests are presented in Section 5.3 of the original text. Key findings include:

- Reliability: The overall Cronbach's alpha was 0.815, and for individual constructs, values ranged from 0.713 to 0.862, all exceeding the 0.7 threshold, indicating high internal consistency. Composite Reliability (CR) values ranged from 0.881 to 0.982, further confirming reliability.
- Validity: The KMO measure was 0.958, and Bartlett's test was significant ($p < 0.001$), confirming the data's suitability for factor analysis. The Average Variance Extracted (AVE) for all constructs exceeded 0.5 (ranging from 0.669 to 0.949), demonstrating satisfactory convergent validity. Discriminant validity was also established (details not shown in original but implied by successful CFA).

Table 3 – Reliability & Validity Indicators (CFA)

Test	Result	Acceptable Criteria	Status
Cronbach's Alpha (Overall)	0.815	>0.70	Acceptable
Cronbach's Alpha (Construct Range)	0.713–0.862	>0.70	Acceptable
Composite Reliability (CR)	0.881–0.982	>0.70	Excellent
KMO	0.958	>0.60	Excellent
Bartlett's Test	p < 0.001	p < 0.05	Significant
AVE Range	0.669–0.949	>0.50	Good

5.3 Structural Model and Hypothesis Testing

The initial structural model (M2) showed suboptimal fit indices ($\chi^2/df = 3.566$, CFI = 0.830, RMSEA = 0.069). Based on modification indices, covariances were added between error terms of a few measurement items that shared similar wording or context, resulting in the final model M3. This modified model demonstrated an excellent fit to the data ($\chi^2/df = 2.343$, GFI = 0.890, CFI = 0.925, TLI = 0.914, RMSEA = 0.050, RMR = 0.038), meeting all acceptable criteria.

The standardized path coefficients and their significance for the final model (M3) are reported in Table 7 (original text) and summarized here with hypothesis testing:

1. Antecedent Perceptions:
    - Cost Perception had strong, significant negative effects on both Performance Expectancy ($\beta = -0.810$, $p < 0.001$) and Effort Expectancy ($\beta = -0.832$, $p < 0.001$). H1a and H1b are strongly supported. Higher perceived costs severely dampen expected benefits and increase perceived difficulty.
    - Technology Perception had a very strong positive effect on Facilitating Conditions ($\beta = 0.848$, $p < 0.001$). H2 is strongly supported. Confidence in the technology is closely linked to the belief that supportive conditions exist.
    - Policy Perception had a strong positive effect on Social Influence ($\beta = 0.738$, $p < 0.001$). H3 is strongly supported. Visible and favorable government policies create a social environment conducive to adoption.
2. Core UTAUT Paths:

- All three antecedents to Behavioral Intention were significant: Social Influence ($\beta = 0.424$, $p < 0.001$) had the strongest effect, followed by Effort Expectancy ($\beta = 0.301$, $p < 0.01$) and Performance Expectancy ($\beta = 0.253$, $p < 0.001$). H4, H5, and H6 are supported.
- Both Behavioral Intention ($\beta = 0.347$, $p < 0.001$) and Facilitating Conditions ($\beta = 0.582$, $p < 0.001$) had significant positive effects on Use Behavior. H7 and H8 are supported. Notably, the effect of Facilitating Conditions was substantially larger than that of Intention.

Table 4 – Model Fit Indices (M2 vs M3)

Fit Index	Value	Threshold	Status
χ^2/df	3.566	< 3.0	Marginal
CFI	0.830	> 0.90	Poor
RMSEA	0.069	< 0.08	Moderate

Table 5 – Path Coefficients & Hypothesis Testing

Hypothesis	Path	β (Standardized)	p-value	Result
H1a	CP → PE	-0.810	<0.001	Supported
H1b	CP → EE	-0.832	<0.001	Supported
H2	TP → FC	0.848	<0.001	Supported
H3	PP → SI	0.738	<0.001	Supported
H4	PE → BI	0.253	<0.001	Supported
H5	EE → BI	0.301	<0.01	Supported
H6	SI → BI	0.424	<0.001	Strongly Supported
H7	FC → UB	0.582	<0.001	Strongly Supported
H8	BI → UB	0.347	<0.001	Supported

5.4 Membership Degree Analysis of Key Constructs

To identify the most influential specific indicators within the key constructs, a membership degree analysis was conducted (Section 6, original text). Key insights include:

- For Facilitating Conditions, the strongest indicator was the belief that operational problems could be promptly resolved through support channels (D4, score 0.69), followed by awareness of incentive policies (D1).
- For Social Influence, the belief that local governments and enterprises were actively promoting DRPV (C3, score 0.69) and having relatives/friends who had already adopted (C2, score 0.69) were equally strong.
- The most effective antecedent to Social Influence was the establishment of physical, local government service centers for consultation (I1, score 0.72).
- Under Performance Expectancy, reducing electricity bills (A1) and improving air quality (A5) were equally prioritized, highlighting the dual importance of economic and environmental benefits.

Table 6 – Membership Degree Analysis

Construct	Indicator	Membership Score	Rank
Facilitating Conditions	D4 (Problem resolution support)	0.69	1
	D1 (Policy awareness)	— (mentioned as 2nd)	2
Social Influence	C3 (Govt & enterprise promotion)	0.69	1
	C2 (Relatives/friends adopted)	0.69	1
Policy Perception → Social Influence Antecedent	I1 (Local service centers)	0.72	Highest
Performance Expectancy	A1 (Electricity bill reduction)	— (ranked equal 1st)	1
	A5 (Air quality improvement)	— (ranked equal 1st)	1

6. Discussion

This study yields several important findings that advance our understanding of rural DRPV adoption and have significant implications for policy and practice.

First, the primacy of Facilitating Conditions over Behavioral Intention is a pivotal finding. While intention matters, the actual participation behavior is more strongly governed by the perceived availability of institutional, technical, and infrastructural support (β = 0.582 vs. 0.347). This underscores that rural residents are pragmatic; a positive attitude alone is insufficient if the system is perceived as complex, unsupported, or risky to operate. This finding aligns with the practical challenges noted in rural energy literature (Aklin et al., 2018; Yadav et al., 2020) and emphasizes that "making it easy" is as crucial as "making it desirable." The strong link between Technology Perception and Facilitating Conditions (β = 0.848) further indicates that building public confidence in the technology itself is foundational to creating a sense of support.

Second, Social Influence is the most powerful driver of Behavioral Intention, surpassing even the expected performance and ease of use. This highlights the profoundly collectivist and community-oriented nature of decision-making in rural Chinese contexts (Wang et al., 2023). Adoption is not merely an individual cost-benefit calculation but a social process. The influence stems from two main sources: horizontal peer influence (neighbors, friends adopting) and vertical authoritative influence (government and enterprise promotion). The finding that on-site, local government consultation centers (I1) are the most effective policy perception tool for boosting social influence is critical. It suggests that in rural areas, tangible, localized, and interpersonal forms of communication and trust-building trump broad, impersonal media campaigns. This corroborates Yadav et al. (2020), who found rural residents preferred word-of-mouth and village-level programs over electronic media.

Third, Cost Perception acts as a critical barrier, exerting strong negative pressures on both the perceived benefits and ease of DRPV systems. The high negative coefficients (-0.81, -0.832) reveal a deep-seated sensitivity to financial outlay and risk among rural households, consistent with their documented risk aversion (Wu et al., 2023). This perception is not just about the sticker price but encompasses fears of hidden costs, fraud, and uncertain returns. The merger of risk into cost perception during model refinement validates this broader conceptualization of financial apprehension.

Fourth, the dual valuation of economic and environmental benefits within Performance Expectancy is noteworthy. Contrary to some narratives that prioritize economics for low-income groups, rural residents in this sample placed equal weight on saving money and contributing to environmental protection ("green, low-carbon"). This suggests that promotional messages should not solely focus on financial returns but can legitimately and effectively appeal to environmental pride and collective responsibility for clean energy.

Finally, the methodological contribution of integrating online text mining with traditional survey-based SEM is validated. The online analysis successfully identified salient, real-world concerns (e.g., contract pitfalls, technical components, specific pilot counties) that informed the development of context-specific perceptual constructs. This bottom-up approach enriched the UTAUT model, making it more grounded and relevant to the specific case of rural DRPV in China.

7. Conclusion and Policy Implications

7.1 Conclusion

This research set out to systematically identify and validate the key drivers influencing rural residents' participation in county-wide distributed rooftop photovoltaic (DRPV) projects in China. By employing a novel mixed-methods approach that dynamically mined online public discourse and integrated the findings with the established UTAUT framework, the study developed and empirically tested a comprehensive behavioral model.

The results clearly demonstrate that rural DRPV adoption is a complex process governed more by practical enablers and social norms than by individual attitude alone. Facilitating Conditions—shaped by positive Technology Perception—are the most critical determinant of actual participation. Social Influence—amplified by clear and locally communicated Policy Perception—is the strongest shaper of adoption intention. Meanwhile, Cost Perception remains a formidable, multifaceted barrier that diminishes both expected benefits and perceived ease. Rural residents evaluate DRPV through a lens that equally values economic utility and environmental contribution.

7.2 Policy Implications

Based on these findings, a multi-layered policy and promotion strategy is recommended to accelerate rural DRPV diffusion:

1. Fortify Facilitating Conditions through Robust "Lifecycle Support":
    - Establish and publicize localized, one-stop service centers in townships or large villages. These centers should provide consultation, contractor vetting, contract guidance, and a clear helpdesk for post-installation issues. This directly addresses the top concern about problem resolution.
    - Develop and subsidize local operation and maintenance (O&M) networks, perhaps training local technicians, to ensure long-term system performance and build trust.
    - Simplify and standardize grid connection procedures and financing applications to reduce bureaucratic effort expectancy.

2. Amplify Social Influence through Community-Centric Mobilization:
    - Launch "Pioneer Village" or "Model Household" programs that publicly recognize and reward early adopters. Peer demonstrations are powerful.
    - Engage village committees and local leaders as credible advocates and channels for information dissemination. Endorsement from trusted local authorities is crucial.
    - Facilitate community meetings and site visits to existing installations, leveraging the power of interpersonal communication and observation.
3. Mitigate Cost and Risk Perception through Targeted Financial Instruments:
    - Design subsidy schemes that reduce upfront capital burden (e.g., direct equipment grants, discounted loans). Partner with rural credit cooperatives to offer green loans with favorable terms.
    - Promote clear, standardized, and government-vetted contract templates to protect residents from fraud and hidden clauses. Consider insurance products to guarantee performance.
    - Provide transparent, personalized ROI calculators to help households understand long-term benefits versus costs, combating short-term risk aversion.
4. Craft Integrated Communication Campaigns:
    - Messages should highlight both "saving on your electricity bill" and "powering a cleaner village."
    - While utilizing new media platforms, ensure content is tailored for rural audiences and complemented heavily with offline, person-to-person engagement through the service centers and community events.

7.3 Limitations and Future Research

This study has limitations that point to future research directions. The sample, while representative of potential early adopters, over-represents higher-income and educated rural residents. Future studies should intentionally sample a broader socioeconomic spectrum to explore how drivers may vary across income, education, and age groups, enabling differentiated policy design. The online data, though extensive, may not fully represent the views of the offline or digitally excluded rural population. The study is also geographically focused on one province in China. Comparative studies across different regional contexts (e.g., less developed western provinces) or different countries would be valuable to test the generalizability of the model and identify context-specific moderators.

In conclusion, accelerating the rural energy transition via DRPV requires moving beyond generic subsidies. It demands a nuanced, socially intelligent approach that builds reliable support systems, harnesses the power of community, directly addresses financial anxieties, and communicates through trusted local channels. This study provides an empirical roadmap for such an approach.

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