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Adoption and Diffusion of Residential Photovoltaics under Heterogeneous Behaviors

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Abstract: Driven by global sustainability goals, residential photovoltaic (PV) has become a key driver in achieving carbon neutrality. Residential PV systems, due to their low cost and ease of installation, are gaining increasing significance. However, uneven regional development in China has posed challenges.This study, based on consumer behavior theory and supported by text analysis, designed a survey to explore significant internal perception factors influencing PV adoption. Hypothesis testing confirmed the importance of these factors. Using agent-based modeling, we incorporated these significant internal perceptions and demographic attributes, along with external factors such as information dissemination, to simulate consumer decision-making and the effectiveness of promotional strategies.The results show that positive perceptions of benefits, ease of use, and lower risk significantly enhance the willingness to adopt PV systems. Furthermore, controlling the scope of information dissemination and leveraging weak ties (such as online networks) are crucial for improving promotional effectiveness. This research offers practical insights for optimizing PV marketing strategies, aiding both China’s and global green energy transitions.

Keywords: Sustainability, Business statistics, Consumer behavior, Household photovoltaic, Promotion strategy.

1. Introduction

Since 2006, China has been the world's largest emitter of CO2, with its current emissions surpassing the combined total of OECD countries, making carbon reduction a pressing issue. In response, China has committed to peaking carbon emissions by 2030 and achieving carbon neutrality by 2060. With nearly 90% of China's carbon emissions coming from the energy sector, a green and low-carbon energy transition is crucial to reaching these "dual carbon" goals.

Against this backdrop, residential power, known for its cost-effectiveness and cleanliness, has become a key force driving China's energy transition. As of 2022, the newly installed photovoltaic (PV) capacity has surpassed wind power, making it the mainstay of green energy growth. With the low costs and fast installation, household PV systems are becoming important to distributed energy

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demand. Household PV systems provide technological support for achieving "dual carbon" goals by improving the efficiency of decentralized energy use. However, China's household PV development faces significant regional imbalances. According to statistics from the National Energy Administration, Henan, Hebei, and Shandong account for 76% of the country's household PV capacity. These provinces are experiencing diminishing high-quality rooftop resources, while southern regions lag in development, opening up new growth poles has become a pressing issue for sustained market health.

China has implemented the "countywide promotion" policy to promote household PV in southern regions, aiming to develop rooftop PV systems on a large scale to increase energy consumption capacity and coverage. Liling City, a pilot area for household PV in Hunan Province, provides valuable insights for PV promotion in the south. The city's hilly landscape and residential architecture are similar to those of other southern regions, and its successful strategies could guide other pilot areas, supporting the creation of new growth poles.

This study begins by designing a questionnaire based on consumer behavior theory to quantify consumers' subjective perceptions of household photovoltaics (PV) and identify key factors influencing their willingness to install. Using survey data, we apply an agent-based simulation model, integrating subjective perceptions with objective information, to simulate the impact of information dissemination within real social networks on PV adoption. The aim is to provide empirical evidence for promoting residential PV in southern China and offer insights for policy formulation to help achieve the national "dual carbon" goals.

2. Literature Review

As the pursuit of "dual carbon" objectives intensifies, the determinants of household PV installations, alongside the effects of information dissemination on PV diffusion, have gained significant traction in academic discourse. Current research primarily leverages the Technology Acceptance Model (TAM) and Perceived Risk Theory (PRT) to design questionnaires that examine factors shaping consumer adoption of new energy technologies, while capturing subjective consumer data. However, the comprehensive integration of these theoretical frameworks with the nuanced attributes of products remains limited.

In addition, while extant studies often utilize survey data to identify core factors driving consumption decisions and imbue simulation models with heterogeneous consumer characteristics, they frequently neglect the dynamic interplay between subjective perceptions and agent interactions, focusing predominantly on objective consumer data.

2.1. The correlation between the intention of household photovoltaic installation and its influencing factors

The theoretical and methodological approaches to studying household PV installation intentions and influencing factors must balance discussions on consumer acceptance of new technologies and general consumer behavior. This is because the topic of "household PV" involves developing and manufacturing specialized equipment such as new energy batteries and integrated installation of power generation systems—technologies closely tied to consumer acceptance. Moreover, "installation" is a consumer behavior influenced by personal background and cognitive levels.

As a result, most studies are based on the Technology Acceptance Model (TAM) and Perceived Risk Theory (PRT). Using TAM as the theoretical foundation, Ruey-Chyn Tsaur and Hsuan Yi [1] examined factors influencing consumer purchase intentions and found that perceived usefulness and ease of use must work synergistically to influence installation intentions positively. Petrovich et al. [2] conducted a discrete choice experiment with potential household PV investors to test whether risk

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would deter potential consumers from investing. The results showed that perceived policy risks significantly reduced installation intentions. Yinjielin et al. [3] integrated key factors from both theories to construct a model studying consumers' intentions and behaviors regarding the adoption of renewable energy technology, confirming that perceived usefulness and ease of use had significant positive impacts on adoption intentions, while perceived risk had a significant negative impact.

2.2. The interaction of different subjects leads to the generative causality of product consumption.

The consumption of renewable energy products is influenced not only by individual intention but also by the interconnectedness and mutual influence among individuals. Consumer perceptions of various factors can shift due to external influences such as policies and public opinion, leading to changes in preferences. Qi Haifeng et al.[4] and Sun Qianlu et al.[5] both confirmed, in various topics related to green low-carbon technologies, that there is often a significant gap between intention and behavior in practice. Liang Yucheng and Jia Xiaoshuang [6] also pointed out that research has gradually shifted from the relationship between intention and influencing factors to the generative causality of system behavior triggered by multi-agent interactions.

The key to simulating the dynamic process of how multi-agent interactions affect consumer purchasing decisions lies in choosing the appropriate simulation method. Among these studies, the Bass diffusion model is widely applied. Lado Kurdgelashvili et al. [7] and Nicholas Willems et al. [8] optimized the Bass diffusion model by incorporating information diffusion among groups and external influences to explore the diffusion patterns of household PV (e.g., factors and mechanisms influencing adoption rates). Du Huibin et al. [9] argued that the model relies on the assumption of rational actors, where individual preferences are homogeneous, and the aggregate behavior of individuals closely mirrors real market outcomes. However, this model overlooks the heterogeneity of consumer preferences in reality, a gap that the Agent-Based Model (ABM) can effectively address. Minhyun Lee and Taehoon Hong [10] used household survey data to parametrize ABM. They found that the most effective way to enhance PV promotion efficiency is through a combination of export tariff regulations and PV investment incentives. Schiera et al.[11] employed the ABM framework to simulate urban environments, assigning attributes to different households based on social, technological, and economic factors to predict PV installation under various policy models and intensities. Results showed that promoting PV in multi-unit housing (i.e., community buildings composed of single-family homes) is key to widespread adoption.

2.3. Research Gaps

While domestic and international scholars have provided a solid foundation for studying household PV installation intentions and behavioral responses, gaps remain. First, survey questionnaire design for studying intention and influencing factors is often too general, failing to integrate theoretical measurement scales with the internal and external characteristics of household PV systems (e.g., the item "I think household PV is easy to use" does not capture the realities of PV installation, usage, and maintenance). This affects the data's validity and the research's practical value. Second, research exploring the impact of information dissemination on consumer behavior tends to rely on objective consumer demographics—such as gender, age, and income—as differentiating factors, with little attention paid to the critical psychological variables in consumer perceptions. Consequently, further investigation into household PV adoption behavior is required, and strategies for promoting these systems demand deeper exploration.

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3. Methodology

To address these gaps, this study adopts a mixed-method approach, combining survey data collection and experimental investigation to explore the influence of information dissemination on household PV installation and the diffusion of new energy technologies.

First, we employ a questionnaire survey to assess the factors affecting PV installation intentions in Liling City. A proprietary scale was developed to measure subjective consumer perceptions and gather demographic data through a mixed-method sampling strategy that integrates both online and offline data collection. Following this, in the experimental phase, consumer perceptions and background data were leveraged to simulate rural social networks within China. By establishing control and experimental groups within these networks, we examine the influence of varying conditions of information dissemination—specifically, the type and frequency of PV-related information sources—on the willingness to install household PV systems, observing installation rate fluctuations and discerning the underlying patterns.

3.1. Research Hypotheses and Research Instruments Design

3.1.1. Theory and Research Hypotheses

This research employs theoretical models and hypotheses grounded in TAM and PRT to design measurement scales, referencing well-established scales from authoritative sources in related literature. The Technology Acceptance Model (TAM) is commonly used to study consumer behavior toward innovative technologies. As explained by Yinjielin et al.[3], perceived usefulness and perceived ease of use are the primary measures in TAM, referring to an individual's belief that using a system will improve their performance and quality of life and that the system or technology is easy to use or master. Ruey-Chyn Tsaur and Hsuan Yi [1] found that perceived usefulness and ease of use significantly and positively influence installation intentions and behavior.

Within the TAM framework, this study examines perceived usefulness and ease of use and further refines perceived usefulness into perceived environmental and financial benefits, considering the specific characteristics of household PV products. This distinction allows for a more accurate capture of consumers' subjective valuation and objective perception of PV installation benefits. Based on this, the following hypotheses are proposed:

H1: Perceived environmental benefit positively influences household PV installation intention.

H2: Perceived financial benefit positively influences household PV installation intention.

H3: Perceived ease of use positively influences household PV installation intention.

Bauer extended the concept of perceived risk from psychology, which later evolved into Perceived Risk Theory (PRT). The academic community widely acknowledges Ostlund's [12] suggestion to integrate perceived risk into the intrinsic characteristics of new products. Given that household PV systems involve advanced technologies such as photovoltaic cells, energy storage, and intelligent control, they are considered high-tech products compared to coal-fired power. Therefore, consumers' risk preferences and perceptions largely influence installation intentions and behaviors for household PV systems. Petrovich et al. [2] showed that higher levels of perceived risk significantly reduce the willingness to invest in household PV. Accordingly, this study includes perceived risk as a factor in the questionnaire and proposes the following hypothesis:

H4: Perceived risk negatively influences household PV installation intention.

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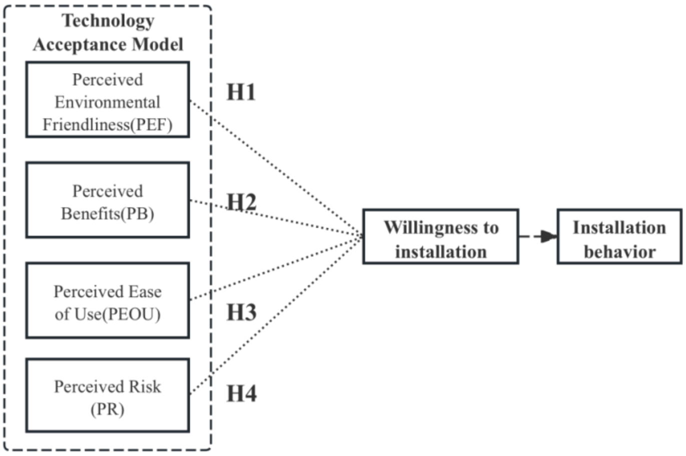

Figure 1: diagrammatic figure

3.1.2. Research Instruments Design

After completing the theoretical model design, this study employs text-mining techniques to analyze consumers' concerns about household PV products deeply. This is the basis for optimizing the questionnaire design, ensuring that the survey items reflect the theoretical model's key elements and the product attributes that consumers care about.

Specifically, Python was used to scrape review data from 2017 to 2022, followed by data cleaning, tokenization, and stopword removal, resulting in 1,485 valid reviews.

Then, the Latent Dirichlet Allocation (LDA) topic model was applied to analyze the text data and identify the product attributes most relevant to consumers. The LDA model, a three-layer Bayesian probability-based model, assumes that documents are composed of topics, and topics are generated from word distributions.

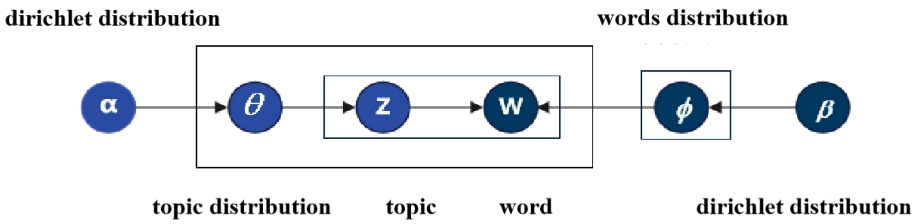

Figure 2: LDA Topic Model

In the figure, the distributions follow a Dirichlet distribution. Based on Gibbs sampling, we set the hyperparameters $\alpha = 50$ and $\beta = 0.01$.

Finally, using equations (1) and (2), we calculated the perplexity under different numbers of topics and determined that 31 was the optimal number of topics. For each subject, we extracted the most frequent keywords.

$$\text{Perplexity}\left(D_{test}\right) = \exp\left\{\frac{-\sum_{d=1}^{M}\log\left(p(w_d)\right)}{\sum_{d=1}^{M}N_d}\right\} \tag{1}$$

$$p(w_d) = \sum_{z} p(z)p(w \mid z, r) \tag{2}$$

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These keywords were used to formulate the items in the questionnaire, ensuring that the content accurately reflects consumers' core needs and concerns. At the same time, the abstract concepts from the theoretical model were organically integrated with the actual product attributes, making the questionnaire both relevant and grounded in consumer perceptions.

Table 1: LDA Model “Topic-Word” Distribution

Subject number	Subject content	Subject identifier
TOPIC3	Canopy villa machine strength installation quality roof use	Range of application
TOPIC5	Delivery logistics quality television transport packaging effect practical	Logistics
TOPIC6	Quality product seller manufacturer store quality capacity merchant	Brand Effects
TOPIC7	Insulation waterproof cooling product service shading performance	Architectural attribute
TOPIC18	Material residential-panel craftsmanship glass wiring details weight bracket	Quality of fittings
TOPIC19	Affordability product price trial quality project installation work	Price
TOPIC22	Usage endurance electricity-generation subsidy installation recommendation process product	Benefits and subsidies
TOPIC23	Installation efficiency electricity-generation lighting housing quality professional care	Installation services
TOPIC24	Test electrical appliance quality cellphone power supply charging power self-generation	Convenience for self-use

Based on the constructs of TAM and PRT used by previous scholars[13-21], combined with text analysis of consumer concerns about residential PV products, the final measurement scale was designed to capture respondents' attitudes and perceptions toward various factors.

3.2. Data Sources

The study employed rigorous sampling techniques to obtain primary market research data. The sample size was determined based on a 95% confidence interval, a 5% margin of error, a design effect (deff) of 2, and an anticipated 92% response rate.

$$n_0 = \frac{u_\alpha^2 p(1-p)}{d^2} = 113.10 \tag{3}$$

$$n_1 = n_0 \times \text{deff} = 113.10 \times 2 = 226.20 \tag{4}$$

Data collection was conducted using a three-stage probability proportional to size (PPS) sampling method, coupled with simple random sampling, encompassing 19 rural and urban streets in Liling City, Hunan Province. First, each township/street served as a Primary Sampling Unit (PSU), and PPS sampling was conducted based on the number of households. Next, secondary units were randomly selected from each chosen PSU. Finally, the target households for the survey were determined using a random number generator from the secondary units. To ensure operational feasibility, the research team collaborated with the local government to organize the respondents, guiding them through the questionnaire process to improve the accuracy and completeness of data collection.

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3.3. Analytical Methods

3.3.1. Hypothesis testing analysis

After conducting the survey and collecting data using a three-stage sampling method that combines Probability Proportional to Size (PPS) and simple random sampling, we first applied stepwise regression analysis to explore the relationships between household PV installation intentions and influencing factors.

Stepwise regression allows the gradual introduction of new variables while removing insignificant ones, thereby establishing the optimal regression equation. This method primarily focuses on forward selection and backward elimination, which typically results in a well-fitted model. Using this approach, we modeled the relationship between installation intention and its influencing factors, and the resulting regression equation is as follows:

$$\mathrm{INT}_{i,t} = \beta_0 + \beta_1 \mathrm{PEF}_{i,t} + \beta_2 \mathrm{PB}_{i,t} + \beta_3 \mathrm{PEOU}_{i,t} + \beta_4 \mathrm{PR}_{i,t} + \varepsilon \tag{5}$$

3.3.2. Main modeling and simulation

The ABM model was then employed to simulate changes in consumer behavior before and after exposure to critical PV installation-related information. ABM is a type of computational model commonly used to simulate the behaviors and interactions of agents, assessing their impact on the overall system[22].It comprises Agent granularity, decision heuristics, adaptive processes, interaction topology, and the environment. ABM captures complex interaction rules and considers agents' varying attributes, different objective functions, bounded rationality, and learning abilities, making it particularly suitable for modeling the diffusion of innovative technologies. Therefore, we employed the ABM framework for system modeling and experimental investigation to explore the impact of user interaction behavior on household PV installation. The specific design is as follows:

First, we used personal data from the second part of the questionnaire to define heterogeneous agents. The same data was used to calculate the similarity of social attributes among agents, and based on the strength of relationships, we built a small-world network to simulate the social network status of individuals in real life. Next, the data from the first part of the questionnaire was used to initialize each Agent's perception levels (Perceived Benefit - PB, Perceived Ease of Use - PEOU, Perceived Risk - PR) and installation intention. Then, following the research of Du Huibin et al. [9], we designed rules for public opinion dissemination, using a unified function to model information transmission, transfer, and learning between connected agents, causing changes in their perception levels during the process. Finally, the change in perception levels was applied to the PV installation intention expression obtained from the questionnaire, and the intention values were recalculated. If the updated intention value of an agent exceeded a pre-defined threshold, the Agent was considered to engage in PV installation.

Due to the inherent randomness in simulation processes, each iteration involved 10 simulations, and the average of the 10 simulation results was used as the outcome for that iteration. In one round of the experiment, the model iterated 192 times, with every 2 iterations representing one month, meaning that each experiment simulated the period from January 2023 to December 2030. Sensitivity analysis was then conducted by varying the network connections for each Agent in multiple experiments, predicting the number of households installing PV systems under different parameter settings. The specific implementation process consists of the following three steps:

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3.3.2.1. Building the Social Network

3.3.2.1.1. Agent Attributes

The Watts and Strogatz [23] WS model is a small-world network with a high clustering coefficient and short average path length. Zhu Yueji [24] demonstrated that the social networks of rural households in China can be regarded as small-world networks. On the one hand, rural households frequently interact with rapid information dissemination, and administrative villages are composed of several small groups with fixed social circles, leading to a high clustering coefficient. On the other hand, different groups establish connections through village meetings, marriages, and other social activities, increasing network connectivity and reducing the number of intermediaries required to transmit information between any two households, thus exhibiting a short average path length.

Following the research of Qiu Zeqi and Huang Shiman [25], we applied the classic WS small-world network model to generate a ring-lattice network containing N = 230 nodes. Each node is connected to its n = 46 nearest neighbors on the ring, and this network served as the basis for subsequent experimental rounds. The personal information and perception levels (ranging from 1 to 5) collected from the questionnaire were then assigned as attributes to each node, thus defining heterogeneous agents.

3.3.2.1.2. Connections with Other Agents

Using the "strong and weak ties theory," we designed a mechanism to identify "close friends" and "acquaintances" within the small-world network to establish connections among the agents[26] . "Close friends" refer to strong ties such as family members, close friends, and neighbors, while "acquaintances" include weaker ties like sales personnel and online reviewers of household PV systems. This distinction between strong and weak ties helps accurately simulate the dynamics of information flow within the social network.

Specifically, the social heterogeneity between agents is calculated using the personal information obtained from the second part of the questionnaire and the Euclidean distance in Blau space. The calculation formula is as follows:

$$\Delta_{i,j} = \sqrt{\sum_{i,j\in X} (S_i - S_j)^2}$$

$$= \sqrt{(Gen_i - Gen_j)^2 + (Age_i - Age_j)^2 + (Edu_i - Edu_j)^2 + (Inc_i - Inc_j)^2 + (Occ_i - Occ_j)^2} \quad (6)$$

In this context, S_i and S_j represent the social background variables of agents i and j, respectively (such as gender, age, education, income, etc., as included in the second part of the questionnaire).

Next, for any agent i, if the $\Delta_{i,j}$ is below a pre-defined similarity threshold, agent j is added to agent i's close friends set R_F. The remaining group of agents is categorized as acquaintances. R_{AS}. Then, from R_F, we randomly select x close friends based on their income levels and from R_{AS}, we randomly select y acquaintances. Finally, the close friends (R_f) and acquaintances (R_a) together form agent i's social network. In this setup, $\Delta_{threshold}$=3, with the initial values of x = 4 and y = 8.

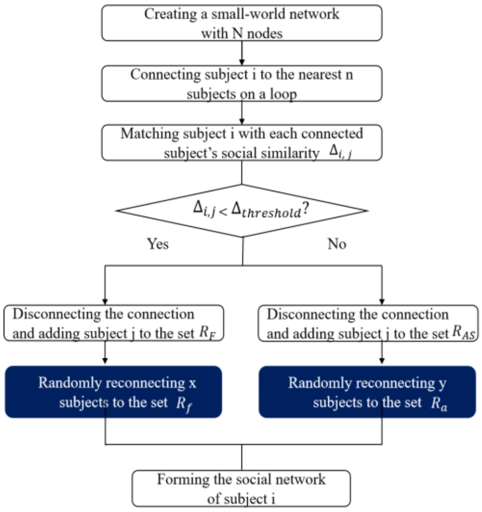

Figure 3: Iterative process for identifying close friends and acquaintances of the subject

3.3.2.2. Designing Information Dissemination Rules

We mainly describe the impact of information dissemination on perception using two mechanisms: attitude uncertainty and attitude overlap. To illustrate this, we take the perceived risk (PR) as an example, while the same rules apply to other variables.

3.3.2.2.1. Attitude Uncertainty Mechanism

In the survey, perception levels were measured using a Likert scale. The closer the score is to 3, the more neutral and uncertain the attitude; conversely, scores closer to 1 or 5 indicate more firm attitudes and lower uncertainty. We assume that the fluctuation range of consumer perception levels follows a normal distribution, as expressed by the following formula:

$$U_{i,t} \sim N(2, 0.1^2) \text{ if } PR_{i,t} \in [2,4] \tag{7}$$

$$U_{i,t} \sim N(1, 0.2^2) \text{ if } PR_{i,t} \in [1,2) \cup (4,5] \tag{8}$$

In this context, $U_{i,t}$ represents the fluctuation range of agent i's perception level at stage t, reflecting the uncertainty of the Agent's attitude. $PR_{i,t}$ represents the perceived risk level of consumer agent i at stage t.

3.3.2.2.2. Attitude Overlap Mechanism

Before being influenced by information dissemination, an agent's perception level lies within the range. During the dissemination process, we compare the perception fluctuation ranges of two agents and calculate the perception overlap (Overlap) between them. The value of Overlap is restricted to a range of 0 to 4. Finally, based on the Overlap, the degree to which the information dissemination influences the perception level of the consumer agent is calculated using the following formula:

$$\text{Overlap}=\min\left(PR_{i,t}+U_{i,t}, PR_{j,t}+U_{j,t}\right)-\max\left(PR_{i,t}-U_{i,t}, PR_{j,t}-U_{j,t}\right) \tag{9}$$

$$\Delta PR_{i,t}=\begin{cases}\dfrac{|\text{ Overlap}_{i,j,t}\text{ }|}{4}\times\left(PR_{j,t}-PR_{i,t}\right), \\ \quad\text{if Overlap}_{i,j,t}>0\text{or} \\ \quad\text{Overlap}_{i,j,t}\leqslant 0\cap j\in R_f \\ 0,\text{ if Overlap}_{i,j,t}\leqslant 0\cap j\in R_a\end{cases} \tag{10}$$

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In this context, R_f and R_a represent the close friends and acquaintances of consumer agent i, respectively.

3.3.2.3. Behavioral Judgment

Based on the designed information dissemination rules, each Agent's perception levels and installation intentions are recalculated after being influenced by the information spread. This allows us to assess their behavior and simulate the technology diffusion process.

Specifically, during each iteration, the influence of close friends and acquaintances on the perception levels of an agent is recorded as $\Delta PEF_{i,t}$、$\Delta PB_{i,t}$、$\Delta PEOU_{i,t}$、$\Delta PR_{i,t}$. These changes in perception are then substituted into the causal relationship equation for household PV installation intention, as explored earlier, to update the agent's installation intention. The applied formula is as follows:

$$INT_{i,t+1} = INT_{i,t} + \beta_1 \Delta PEF_{i,t} + \beta_2 \Delta PB_{i,t} + \beta_3 \Delta PEOU_{i,t} + \beta_4 \Delta PR_{i,t} + \varepsilon \tag{11}$$

After each iteration, if the installation intention (Int) exceeds the behavioral judgment threshold (where an installation behavior is considered to occur if the score for installation behavior factors exceeds 3), we can recognize that a technology adoption decision has been made. To set this threshold, we calculate the average installation intention score of all agents with an installation behavior score greater than 3 based on the survey data, and this value is used as the threshold.

4. Results

The study first aims to explore the consumer perception factors influencing the willingness to install household photovoltaics (PV) and to validate the significance of these factors through hypothesis testing. Subsequently, the subjective perception factors and demographic attributes that significantly influence consumers' installation intentions are used as heterogeneous characteristics of agents to simulate the impact of information dissemination and exchange on consumers' decision-making processes.

4.1. Reliability and Validity Testing

The reliability of the questionnaire was tested using Cronbach's α coefficient. The results show that the overall Cronbach's α was 0.902, with the α values for each factor exceeding 0.8, indicating a high level of internal consistency and stability across the survey.

Regarding validity, the questionnaire was developed based on the Technology Acceptance Model (TAM) and Perceived Risk Theory (PRT) and was further optimized through text mining and actual product characteristics to ensure the rationality of the items. For convergent validity, the composite reliability (CR) of each latent variable exceeded 0.7, and the average variance extracted (AVE) was greater than 0.5, demonstrating strong convergent validity of the scale. The discriminant validity test revealed that the square root of each variable's AVE was greater than the correlation coefficients between variables, supporting the model's strong discriminant validity.

4.2. Descriptive Statistics

4.2.1. Demographic Information

A total of 230 valid samples were collected for this study, yielding a valid response rate of 94.65%. The demographic information is presented in Table 3. A comparison of the gender, age, and education

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level distributions between the population and the sample reveals that the sample distribution closely aligns with the overall population, demonstrating the strong representativeness of the collected data.

Table 2: Demographic information of the sample

Variable	Sample Size	Maximum	Minimum	Mean	Standard Deviation	Median	Variance
Gender	230	2	1	1.435	0.497	1	0.247
Age	230	5	1	2.709	1.113	3	1.238
Education Level	230	6	1	3.513	1.294	3	1.675
Occupation	230	8	1	4.483	2.147	4	4.609
Average annual household income	230	7	1	2.883	1.278	3	1.632

4.2.2. Correlation Analysis

The mean values, standard deviations, and correlation coefficients for each variable are summarized in Table 4. The results reveal significant correlations among perceived ease of use, financial benefit, environmental benefit, perceived risk, and household PV installation intention and behavior. Additionally, the average score for installation intention was 3.8, reflecting general interest in household PV products and relatively high purchase intention among users.

Table 3: Correlation Analysis

Variable	Mean	Standard Deviation	Perceived Ease of Use	Perceived Benefits	Perceived Environmental Friendliness	Perceived Risk	Willingness to Installation	Installation Behavior
Perceived Ease of Use	4.195	0.723	1					
Perceived Benefits	4.062	0.721	0.654***	1				
Perceived Environmental Friendliness	4.462	0.577	0.554***	0.498***	1			
Perceived Risk	3.526	0.732	0.229***	-0.316***	-0.076	1		
Willingness to Installation	3.809	0.947	0.521***	0.588***	0.331***	-0.619***	1	
Installation Behavior	3.249	1.085	0.438***	0.473***	0.263***	-0.503***	0.766***	1
Note: ***, **, * denote the significance levels of 1%, 5%, and 10%, respectively.								

4.3. Stepwise Regression Analysis

In the stepwise regression analysis, installation intention was the dependent variable, while perceived environmental benefit, perceived financial benefit, perceived ease of use, and perceived risk were the independent variables.

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Table 4: Stepwise regression analysis results

	Unstandardized coefficient		Standardized Coefficients	t	P	VIF	R^2	Adjusted R^2	F
	B	Standard error							
Constant	2.835	0.396	0	7.153	0.000***	-	0.559	0.554	F=95.66, P=0.000***
Perceived Risk	-0.567	0.06	-0.438	-9.497	0.000***	1.093			
Perceived Benefits	0.401	0.074	0.305	5.425	0.000***	1.626			
Perceived Ease of Use	0.32	0.073	0.244	4.405	0.000***	1.578			

The regression results indicate that perceived financial benefit and ease of use are positively correlated with installation intention at the 0.001 significance level, whereas perceived risk is negatively correlated with purchase intention. Perceived environmental benefit had no significant impact on purchase intention and was thus excluded during the regression process. ased on these results, the following regression equation was established (Equation 15), and the hypothesis H2 through H5 were confirmed, while H1 was not supported.

$$\mathrm{INT}_{\,i,t} = 2.835 - 0.567\mathrm{PR}_{i,t} + 0.401\mathrm{PB}_{i,t} + 0.320\mathrm{PEOU}_{i,t} \tag{12}$$

4.4. Analysis of the influence of information dissemination on installation behavior based on agent modeling

We will progressively replicate the real market by first analyzing the factors influencing consumers' installation intention, then considering the interactions between consumers (such as information dissemination and exchange), and finally simulating consumer behavior decisions.

4.4.1. Simulation interface design

Further, by simulating consumer interaction behavior, this paper examines how information dissemination influences installation decisions. To this end, NetLogo 6.3.0 was used to implement the simulation model and design the simulation interface (Figure 4).

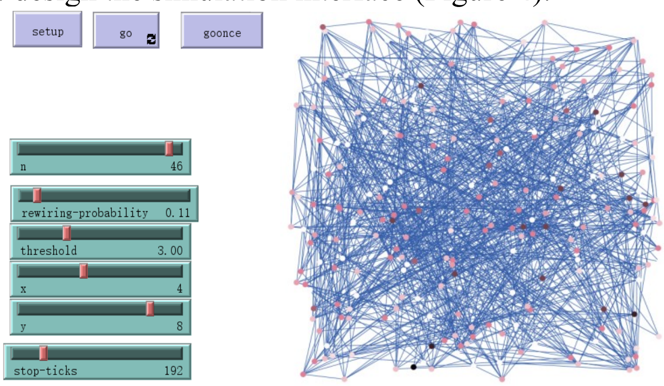

Figure 4: Simulation initial interface

Moreover, the dynamic evolution of social networks and consumer installation behavior can be observed by setting various control variables and parameters. In the simulation process, the subject's

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perception level and installation intention are distinguished by the color depth, and the threshold of installation behavior (4.7467) is set to determine whether there is installation behavior.

Table 5: Simulation control meaning description

Serial Number	Slider Control Name	Meaning Description
1	n	The number of neighbors formed by connecting each node to the closest rules on the ring, with the initial value of n set to 46
2	rewiring probability	The rewiring probability, which means that each node is initially connected to n points, and then with a certain probability, a connection is broken and then reconnected to other random nodes in the network
3	threshold	The set similarity threshold, where subjects j with a similarity below this threshold are added to subject i's friend set
4	x,y	In R_F, randomly generate x friends' income set R_f, and in R_{AS}, randomly generate y acquaintances' income set R_a, with initial values of x=4 and y=8.
5	stop-ticks	The number of iterations per round of experiments, that is, 192 times. In addition, we set that for each iteration, 10 simulation experiments are conducted, and their average value is taken as the result of one iteration

Figure 18 illustrates the network effect of the initial social network after activating the "go" button, showing the evolution over time, including information dissemination, changes in subject perception levels, and updates to installation intentions. The formula for updating installation intention is as follows:

$$\mathrm{INT}_{\,i,t+1} = \mathrm{INT}_{\,i,t} + 0.401\Delta\mathrm{PB}_{i,t} + 0.320\Delta\mathrm{PEOU}_{i,t} - 0.567\Delta\mathrm{PR}_{i,t} \tag{13}$$

Since PEF failed the hypothesis test and was shown to have no significant impact on installation intention, it was not considered a primary attribute. The initial perception level attribute includes only PB, PEOU, and PR. Next, the "set color green" command was used to identify subjects whose installation intention (Int) exceeded the threshold value, marking them in green. The threshold value of 4.7467 was derived from the questionnaire data.

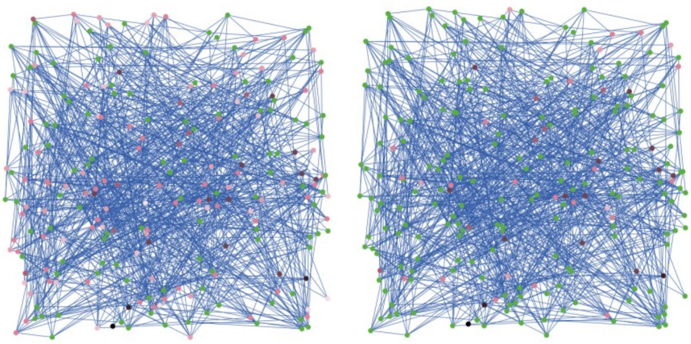

Figure 5: Simulation evolution interface

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4.4.2. Program module function

In the model, several Procedures were designed to establish the behavior rules of the Agents, and the simulation was advanced by repeatedly executing a specific routine or a combination of routines.

Table 6: Key procedures description

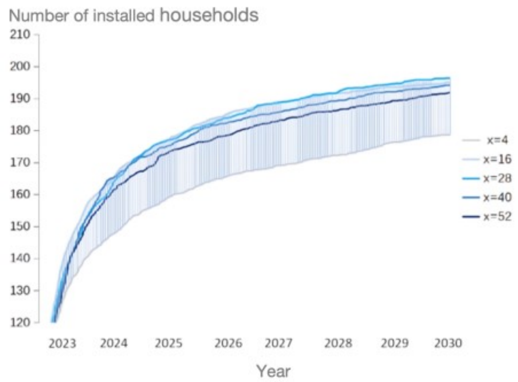
Serial Number	Program Module Name	Function
1	to setup	Initialization
2	to load-globals	Load the Euclidean distance table
3	to go	Run the program
4	to make-edge	Connect to the geographically closest n entities
5	to relink-network	Construct sets of friends and acquaintances
6	to setup-nodes	Build a social network and assign values to each entity's perception level and willingness to install
7	to interact	Calculate the attitude overlap, update the perception level, and determine and display whether each entity will install
8	to setup-smallworld-network	Reconnect network routine, i.e., identify and connect friends and acquaintances based on the threshold
9	to wire-them	Iterate through the turtles

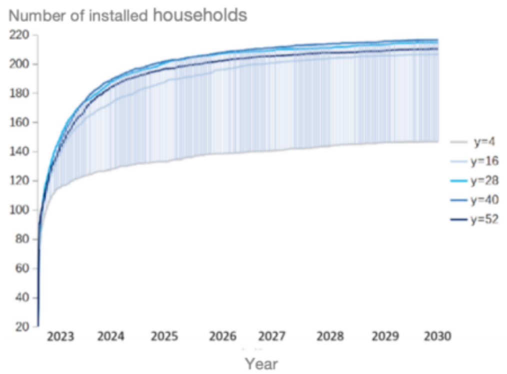
4.4.3. Verification of simulation model

During the model verification process, the simulation prediction results were compared with the official forecast data from the National Energy Administration. In 2023, the official forecast for new distributed photovoltaic installed capacity was 16.67 million kilowatts, reflecting a 35.59% increase. The simulation predicted an increase of 38.51% in PV installed capacity, which closely aligns with the official data, demonstrating the model’s effectiveness.

4.4.4. The impact of information dissemination on the consumption of household photovoltaic products

Then, the impact of the number of connected groups on the level of installed household photovoltaic units (installed capacity) was discussed, and the results were summarized as follows.





(a)Influence of information dissemination among close friends (b)Influence of information dissemination among acquaintances

Figure 6: Different number of close friends and acquaintances under the household photovoltaic technology diffusion path

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First, the saturation level of installed residential photovoltaic households initially increases and then decreases as the number of AC main bodies increases. When the number of "close friends" in the main social network increased from 4 to 28, and the number of "casual acquaintances" increased from 4 to 40, the saturation level of installed households exhibited an upward trend. Subsequently, as the number of "close friends" and "casual acquaintances" continued to grow, the saturation level of installed units began to decline.

Second, the saturation level of installed household photovoltaic units in the "casual friends" information dissemination scenario was higher than in the "close friends" scenario. The number of installed units in the former scenario eventually stabilized at approximately 220, while in the latter scenario, it stabilized at around 210.

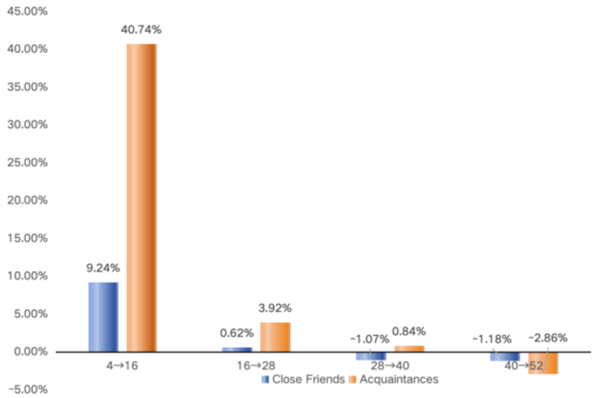

Figure 7: The change in the saturation level of the market with every threefold increase in the number of close friends and acquaintances

Third, information exchange among "casual friends" leads to a faster change in the number of households with PV installations. In general, when the number of "close friends" and "casual friends" increased by 12, the number of installed units showed a significant change under the information exchange scenario among "casual friends," with the largest change reaching 40.74%.

5. Conclusion

This study first analyzed the consumer perception factors influencing household PV installation intentions using hypothesis testing methods. Next, the subjective perception factors and demographic characteristics that significantly impact installation intentions were incorporated as heterogeneous attributes in an agent-based model to simulate the effects of information dissemination and exchange on consumer decisions, leading to the following conclusions:

(1)Higher perceived profitability and ease of use are associated with lower perceived risk and increased installation intentions. The findings indicate that consumers' intention to install PV systems is positively correlated with perceived profitability and ease of use, but negatively correlated with perceived risk. In other words, when consumers perceive significant financial benefits and ease of use, their willingness to install increases substantially, while higher perceived risk reduces their intention. Notably, environmental benefits do not significantly impact installation decisions, underscoring that most consumers prioritize financial returns over environmental advantages.

(2)Expanding the scope of information dissemination initially enhances the effectiveness of promotion, but its impact diminishes over time. During the initial stages, as the number of connected individuals increases, the effectiveness of the promotion improves, and installation rates rise. However, excessive information dissemination leads to increased consumer caution and hesitation, resulting in a decline in the promotion effect. This suggests that there is an optimal range for information dissemination that maximizes the effectiveness of promoting photovoltaic systems.

(3)Information spreads more rapidly through weak ties and contributes to higher installation rates. Information shared among weak-tie groups (e.g., "acquaintances") spreads faster and more widely than among strong-tie groups, thus accelerating technology diffusion. In contrast, strong-tie groups exhibit higher information redundancy and are less receptive to new external information, limiting their role in diffusion. Consequently, the role of weak ties in promoting photovoltaic systems is crucial.

In conclusion, the following suggestions are proposed:

(1) Strengthening institutional guarantees and fostering market trust are crucial for promoting the widespread adoption of residential photovoltaic systems. It is advisable for the government to refine the policy framework, streamline approval processes, and bolster consumer confidence in photovoltaic products. Concurrently, encouraging innovation within the industry, reducing product costs, enhancing technical standards and credit systems, and ensuring high-quality products and reliable after-sales service are essential to diminishing consumer risk perceptions. The integration of institutional safeguards with technological advancements is instrumental in increasing market trust and awareness of photovoltaic products.

(2) Control the scale of information dissemination and optimize public opinion management. The scope and methods of information dissemination are critical to promoting photovoltaic adoption. Governments and enterprises should carefully regulate the scale of promotional activities to prevent information overload while ensuring effective communication. A robust public opinion monitoring mechanism should be established to promptly curb the spread of negative information and ensure that consumers receive accurate and positive product information to enhance the promotional impact.

(3) Leverage weak-tie networks to promote the widespread adoption of photovoltaics. Governments and businesses ought recognize the crucial role of weak-tie networks (such as social media and online platforms) in technology diffusion and use diversified communication channels to reach potential consumers across social boundaries. Innovative marketing strategies should be encouraged to increase awareness and installation rates of photovoltaic products, utilizing modern communication tools. Additionally, attention must be given to the cost-effectiveness and efficiency of promotional strategies, avoiding over-reliance on strong-tie networks.

Future policy design should consider changing social influences. Monitor changes through longitudinal studies and adjust policies dynamically.

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