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Research paper

Consumer Perception and Willingness to Pay for Solar Energy: A Behavioral Analysis

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Abstract

Transitioning to renewable energy is essential for sustainability and mitigating climate change. This examine examines consumer notion and willingness to pay for solar electricity through a stratified random sampling of 385 respondents. Statistical techniques, together with exploratory information evaluation, correlation analysis, logistic regression, and group comparisons, diagnosed key predictors of sun adoption. Results show that environmental concern is the most powerful motive force (coeff = 0.2348, p = zero.013), followed by the notion of carbon emission discount (coeff = 0.2128, p = 0.028). Surprisingly, government subsidies (p = zero.650) and training stage (p > 0.280) no longer notably affect adoption. Lower-profits companies exhibit better hobby (coeff = 0.5279, p = 0.096), in all likelihood due to subsi-dy reliance. Pricing transparency is likewise critical, as receiving a solar fee quote correlates strongly with adoption (r = 0.50). These findings spotlight the need for focus campaigns, monetary accessibility, and obvious pricing strategies to boost solar adoption.

Keywords: *Consumer-Decision-Making; Environmental Awareness; Green Energy; Predictive Modeling; Willingness to Pay.*

1. Introduction

With increasing concerns over environmental sustainability, the discussions on carbon taxation, agricultural waste management, and consumer willingness to pay (WTP) for eco-friendly initiatives have gained immense momentum. According to a study in [1], Italian citizens are willing to pay an average annual amount of €101 to €154, which works out to a fuel tax from €0.17 to €0.30 per liter, while the acceptance is higher when applied to funding environmental projects. Similarly, WTP of farmers for sustainable AWM in Ethiopia and found a mean WTP of 6.84 labor days (273.50 Birr) or 8.20 Birr in monetary value which is influenced by age, education, and economic conditions, was investigated in [2]. The growing number of climate-induced extreme weather events and energy sustainability challenges has led to concerns over consumer willingness to pay (WTP) for reliable and green electricity solutions. Residential WTP for backup electricity during a 10-day winter blackout in the northeastern USA was studied in [3], finding that households were willing to pay $1.7–2.3 per kWh for private power and $19–29 per day to support community electricity needs. Also, WTP for green electricity in Poland, where renewable energy accounts for 13.5% of total consumption, indicating that age, income, environmental attitudes, and education play significant roles in WTP, was investigated in [4]. However, the mean WTP has remained at $3.5 per month, owing to low GDP per capita and minimal awareness about green energy. Transition to sustainable sources of energy and the reliability of supply of electricity are major concerns for modern economies. Consumer WTP for hydrogen FCEVs in a choice experiment with 1,072 participants was examined in [5]. The results presented that factors that include purchase price, driving range, refueling time, fuel cost, emissions reduction, and refueling accessibility had considerably influenced WTP, and their consumers would spend RMB 20,810 to 95,310 over conventional vehicles in order to go for FCEVs. Similarly, a study in [6] estimated the household WTP to avoid power outages in northwest England, and the willingness of households was found to pay £5.29 to avoid peak-hour outages, £7.37 to shift outages to weekdays, and £31.37 to prevent winter outages. The key aspect in the acceptance of renewable energy infrastructure and residential solar adoption would be towards meeting sustainability goals. The public WTP for renewable energy infrastructure using 2,000 respondents from Germany, Austria, Italy, and Switzerland, indicating a significant increase in acceptance of solar farms at a value of €29.5/month and power-to-gas at €8.5/month, while that for gas power plants and power lines is decreasing, was investigated in [7]. Political endorsements also promoted acceptance, as the Italians reported a positive influence of EU and national bodies (+3.5% and +2.7%). A meta-analysis of residential photovoltaic (PV) adoption was also performed in [8], where socio-demographic factors were found to have minimal effects, whereas perceived benefits, environmental concern, and subjective norms had significant influences on adoption intention ($R^2 = 0.280$). The knowledge of and cost of sustainable living determine willingness to pay. According to [9], consumers with knowledge of the benefits of GB were willing to pay a 9.25% premium, while the developers with experience in GB accepted a 17% premium. Likewise, study in [10] determined that more than 80% of Beijing citizens were willing to pay for the reduction of smog, and WTP was estimated to vary between 615.13 CNY for 30% and 914.49 CNY for 60%, corresponding to 0.55%–0.82% of the annual income. Both studies clearly show that with greater awareness comes a higher WTP, yet financial constraints continue to play an important role. India is at the forefront of the global energy transition, with ambitious targets to achieve 500 GW of non-fossil fuel-based capacity by 2030, including 280 GW from solar energy alone (MNRE, 2023). Key initiatives such as the PM Suryodaya Yojana aim to install rooftop solar in 10 million households, particularly targeting middle- and lower-income groups. Despite the policy push, adoption at the consumer level remains inconsistent across states and income brackets. Factors such as trust in solar products, awareness of financing options, and pricing transparency continue to influence uptake. This study aims to bridge this policy-intent and behavioral gap by analyzing the determinants of solar adoption from a consumer perspective in the Indian context.

This paper is divided into major sections. The Research Objectives define the scope of the study, focusing on consumer awareness, financial considerations, and behavioral influences. The Literature Review assesses existing research on renewable energy adoption, WTP, and other key influencing factors. The Research Methodology discusses the survey design, sample size determination, using Cochran's formula, and adopts stratified random sampling to ensure diverse representation. The Results and Discussion present exploratory analysis from the data, correlation analysis, logistic regression, and group comparisons of key predictors of solar adoption. The Predictive Model for Solar Adoption section applies statistical techniques to distinguish between factors significantly and non-significantly affecting WTP. The Conclusion will summarize key insights into the matter at hand, with environmental awareness, monetary accessibility, and transparent pricing being driving forces of solar adoption.

1.1. Research objectives

This study serves the purpose of exploring the consumer's awareness of and perceptions toward solar energy, including the level of knowledge gathered about its benefits and challenges, as well as the potential for adoption. The other area of focus includes willingness to pay as evaluated by both the financial threshold and factors that drive consumer decision-making. This includes the identification of major behavioral and psychological factors that affect solar adoption, with attitudes, trust, and environmental consciousness as influences of consumer choices. The study is also concerned with analyzing socioeconomic influences, considering such demographics as income, education, and location, affecting perception and WTP. Finally, the research aims to apply statistical and predictive modeling techniques for the derivation of deeper insights using data-driven approaches such as factor analysis, regression models, and machine learning in order to have a better predictive capability for solar energy adoption trends.

2. Literature review

2.1. Regional variation in willingness to pay (WTP)

Willingness to pay (WTP) for renewable energy differs across economic and cultural contexts. In Nigeria, only 5–10% of surveyed consumers were willing to pay more for renewable electricity, with WTP influenced by age, income, and awareness levels [11]. In China, the estimated annual public WTP for solar R&D reached CNY 23.78 million, influenced by education and income but reduced at higher bid levels [12]. Meanwhile, in Ethiopia, 55% of the rural population lacks electricity access, yet grid connections were preferred over solar PV, and WTP was only feasible when installment-based payments were offered [13]. These studies show that even when interest exists, cost structures and perceived utility greatly influence adoption. In contrast, European studies [14] reveal higher variation in WTP for sustainable goods like seafood (ranging from 7% to 40%), largely tied to trust and sustainability communication, emphasizing psychological over purely financial drivers. These patterns offer a global perspective for understanding India, where subsidies exist but WTP may still be constrained by trust, transparency, and economic diversity.

2.2. Behavioral and psychological drivers

Behavioral factors such as environmental concern, risk perception, and subjective norms significantly shape renewable adoption. In China, residents were willing to pay CNY 32.63/month for green electricity when it aligned with health benefits and trust in government policies [15]. In New Zealand, despite minimal government incentives, a choice experiment showed that households would pay 2% more for a 10% increase in renewable supply, reflecting high behavioral engagement even in renewables-saturated contexts [16]. In Australia, consumers were more willing to pay for green restaurants if they had higher environmental awareness (women scoring higher Green Index = 3.29 vs men = 2.66), though men showed higher price acceptance [22]. In Nepal, perception of pesticide risk and personal health history significantly influenced WTP for organic vegetables [26–29]. These studies underscore how perceived benefit, awareness, and trust play critical roles in sustainable choices. Our study aligns with this behavioral literature, finding that environmental concern ($p = 0.013$) and carbon reduction belief ($p = 0.028$) were the most significant predictors of solar adoption, while structural factors like income or location were less relevant.

2.3. Financial constraints and subsidy gaps

Although many countries offer subsidies, financial constraints remain a major adoption barrier. In India, despite schemes like PM Suryodaya Yojana, public awareness and procedural complexity often dilute the impact of subsidies. Our study found that subsidy awareness ($p = 0.650$) did not significantly influence adoption—a finding consistent with [11] and [13], where interest was present but affordability and awareness were barriers. In China, households supported water infrastructure via an 8.3% surcharge, driven primarily by economic capacity rather than environmental concern [19–21]. These results imply that pricing mechanisms must be localized and consumer-informed, not generic or top-down.

2.4. Trust and information barriers

Emerging evidence suggests that trust in technology and institutions is an essential enabler. In the Chinese context, trust in government played a major role in WTP for solar and sponge city programs [15], [20]. In Europe, seafood WTP was strongly tied to product credibility and traceability [14]. In Australia, trust in sustainability claims affected both perception and pricing acceptance [22]. Our survey revealed neutral trust levels in solar technology (Q13: mean = 3.14), which could be due to inconsistent after-sales service, lack of certification, or poor public engagement. Prior studies confirm that certification programs, verified testimonials, and local demonstrations are effective in closing trust gaps—policy actions that are equally relevant for India.

2.5. Identified research gap

Although global studies explore WTP, sustainability perception, and policy impact, much of the Indian literature remains descriptive, focusing on demographics or subsidy access. What's lacking is a predictive, behaviorally anchored framework that combines psychological drivers (e.g., environmental concern, trust) with financial and informational variables to understand real-world adoption. This study fills that gap by applying correlation and logistic regression models to assess the comparative influence of behavioral and financial factors, offering an evidence-based roadmap to support India's rooftop solar mission.

3. Research methodology

A structured research methodology followed, commencing with an exhaustive literature review in order to review the extant studies that pertain to consumer perception, willingness to pay, and adoption of solar energy. This would assist in ascertaining research gaps, specifically about the behavioural, psychological, and socioeconomic influences associated with solar adoption. Consequently, the objectives for the research were framed around these insights-areas of consumer awareness, financial concerns, behavioural effects, and modelling predictions. To attain these goals, questions for the survey were framed in such a way that they aligned with key research objectives. The survey tool consisted of Likert scale, multiple-choice, and yes/no response types to capture varied consumer views. The mapping of the research objectives with the questions framed for the survey and the associated response types are presented in Table 1 to provide a structured framework for collecting and analysing the data.

Table 1: Survey Questions and Type of Responses

Q#	Question	Type of Response
Q1	How familiar are you with solar energy technology?	Likert Scale (1-5)
Q2	Have you heard about government incentives/subsidies for solar energy?	Yes/No
Q3	Which sources of information have influenced your awareness of solar energy?	Multiple Choice (TV, Social Media, Friends, Govt Campaigns, Others)
Q4	In your opinion, how reliable is solar energy compared to conventional electricity?	Likert Scale (1-5)
Q5	How would you rate the availability of information on solar energy products?	Likert Scale (1-5)
Q6	How much extra would you be willing to pay for solar energy compared to conventional electricity?	Percentage (10%-100%)
Q7	If the government offers a 50% subsidy, would you invest in solar panels?	Yes/No
Q8	What is the most important factor influencing your decision to pay for solar energy?	Multiple Choice (Upfront Cost, Long-Term Savings, Govt Incentives, Environmental Benefits)
Q9	How likely are you to invest in solar energy in the next 5 years?	Likert Scale (1-5)
Q10	What financing options would make solar energy adoption easier for you?	Multiple Choice (Loans, Leasing, Govt Grants, Tax Benefits)
Q11	How concerned are you about the environmental impact of traditional energy sources?	Likert Scale (1-5)
Q12	Do you believe that switching to solar energy can help reduce carbon emissions?	Likert Scale (1-5)
Q13	How much do you trust solar energy products to provide reliable electricity?	Likert Scale (1-5)
Q14	Have you faced any misleading information about solar energy?	Yes/No
Q15	What is your primary concern about solar energy adoption?	Multiple Choice (Performance, Cost, Maintenance, Govt Policy)
Q16	What is your age group?	Multiple Choice (18-25, 26-35, 36-45, 46-60, 60+)
Q17	What is your income level?	Multiple Choice (Low, Medium, High)
Q18	What is your highest level of education?	Multiple Choice (High School, Undergraduate, Postgraduate, PhD)
Q19	Where do you reside?	Multiple Choice (Urban, Semi-Urban, Rural)
Q20	Do you own or rent your residence?	Multiple Choice (Own, Rent)
Q21	How likely are you to recommend solar energy to others?	Likert Scale (1-5)
Q22	What is the biggest barrier stopping you from adopting solar energy?	Multiple Choice (High Cost, Lack of Awareness, Lack of Govt Support, Installation Issues)
Q23	Have you ever received a quote for a solar panel system?	Yes/No
Q24	If the payback period for solar energy were less than 5 years, would you adopt it?	Yes/No

3.1. Sample size determination and sampling technique

The formula of Cochran was used in determining this study's sample size, which provides the minimum sample size required based on a specific level of confidence and margin of error. The formula considered statistical power, research objectives, and the population characteristics. This implies that for this study, we used a 95% confidence level, given as Z = 1.96, assumed population proportion at 50%, denoted by p = 0.5, and the margin of error was at 5% as e = 0.05. The minimum number of subjects required for the sample is, therefore, 385 respondents.

$$n_0 = {Z^2 \times p \times (1-p)}/{e^2} \tag{1}$$

To ensure proper random sampling of this consumer group cut across the subgroups, stratified random sampling was adopted. This method guarantees equal representation from all the subsets of demographics involved, preventing biased results from overstating a subgroup.

Stratified Random Sampling allows for a better representation and balance of samples through stratification along a set of key demographic factors such as income level (Low, Medium, High), education level (High School, Undergraduate, Postgraduate), and type of residence (Urban, Semi-Urban, Rural). Respondents are then randomly selected within each stratum in proportion to the actual population as shown in Table 2, ensuring diversity and not over-representing any one group.

Table 2: Summary of Sample Selection Approach

Aspect	Decision
Minimum Sample Size	385 respondents
Target Sample Size	400-500 respondents (to reduce bias & account for non-responses)
Sampling Technique	Stratified Random Sampling
Stratification Criteria	Income Level, Education Level, Residence (Urban/Rural)
Why This Technique?	Ensures equal representation of different consumer segments

To increase the reliability of the study, 400-500 respondents are targeted, which exceeds the minimum required sample size of 385, thereby reducing bias and accounting for potential non-responses, hence making the findings more robust and generalizable. Numerous statistical analyses are conducted further to evaluate the perception and willingness of consumers to adopt solar energy. First, using EDA, the present study investigates how a set of responses is distributed and identifies patterns in the dataset. Correlation analysis is further used to determine if there exists a relationship between key factors influencing solar adoption. Further, logistic regression modelling for the prediction of solar adoption has been carried out based on different socioeconomic and psychological factors. Some of these demographic differences were then analysed using group comparison tests to see whether there existed variations in the results concerning income level, education, or by urban vs. rural residents. Details of results and inferences from these tests are given in subsequent sections.

4. Result and discussion

This section discusses the findings derived from statistical analyses conducted during the study. Results are organized around key research questions, namely: consumer awareness, willingness to pay, behavioural influence, and socio-economic factors determining solar adoption. Each analysis has been described based on the insights of how these variables might determine consumer choice, with detailed interpretation and implications that have been discussed in the subsections below.

4.1. Explanatory data analysis

The dataset consists of 385 respondents with a mix of numerical (Likert scale & percentage-based responses) and categorical (Yes/No, multiple-choice, and demographic details) features were collected. A total of 24 features capture insights on consumer awareness, willingness to pay, investment likelihood, and key barriers to solar energy adoption.

4.1.1. Summary of numerical responses

The core numerical variables' mean statistical summary provides information highlighting major consumer perceptions concerning the adoption of solar energy. Figure 1 illustrates the distribution of major numerical variables. Respondents generally showed moderate familiarity with solar energy (Q1: mean = 3.57) and a high level of concern for environmental impact (Q11: mean = 3.64), both of which are favorable indicators of awareness. However, neutrality in trust toward solar technology (Q13: mean = 3.14) and willingness to invest (Q9: mean = 3.16) suggest that deeper engagement strategies—such as product demonstrations or trust-building campaigns—may be necessary to convert awareness into adoption.

When determining how easily solar energy information is available (Q5), answers indicated a neutral approach by respondents, with the mean being 3.14; hence, access to the required information may not be widespread or readily available. Willingness to pay more for solar energy (Q6) scored a mean of 54.4%, albeit this had a sizeable standard deviation of 26.2%, which suggests vastly different economic psyche. Notably, the consumers who voiced a willingness to pay over 75% more for solar energy indicate an opportunity for targeted financial incentives. The willingness to invest in solar energy over the next five years (Q9) displayed a neutral-to-positive attitude (mean = 3.16). This suggests that although there is some interest, likely external factors such as cost and policy may hinder the ultimate decision. A high degree of concern about the environmental impacts of conventional energy sources (Q11, mean = 3.64) was also recorded, indicating that respondents are broadly aware of the adverse effects of conventional energy consumption. However, trust in solar energy products (Q13) was at a neutral level, mean = 3.14, showing some uncertainty regarding their effectiveness and reliability. Lastly, the probability of recommending solar energy to other people (Q21) was at 3.54, indicating a positive attitude towards advocating for solar solutions. Collectively, these results indicate that although consumers acknowledge the environmental advantage of solar energy, cost, trust, and the availability of information possibly play central roles in allowing consumers to adopt solar solutions.

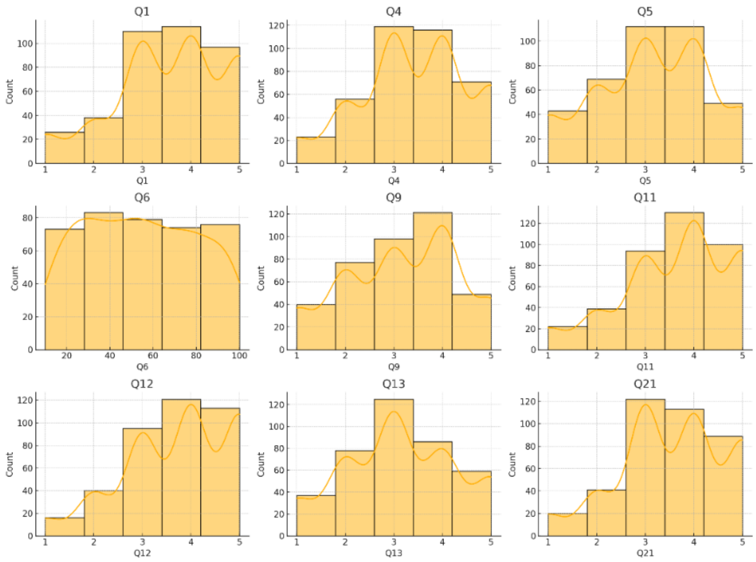

Fig. 1: Distribution of Key Numerical Responses Related to Solar Energy Perception and Behavioral Intent. High Environmental Concern (Q11) and Moderate Familiarity with Solar Technology (Q1) Are Evident. Trust in Solar Energy Systems (Q13) Remains Neutral, and Willingness to Invest (Q9) Reflects Cautious Optimism Among Consumers.

4.1.2. Summary of categorical variables

The summary highlights consumer awareness of the available incentives, key deciding factors, and major barriers towards adopting solar energy. A sizeable 67.5 percent of the respondents, 260 out of 385, indicated that they know about government subsidies for solar energy (Q2), while the majority were aware of existing incentives, it is a concerning proportion that are not aware. When sources of awareness are analyzed, social media takes the lead at 109 mentions, ~28.3%. Government campaigns closely follow this rank. This further indicates that the digital outreach and policy-driven initiatives are essential to educate consumers on solar energy. The key factors driving willingness to pay (Q8) are related to financial aspects. The most important factor for 41.3% (159 respondents) was the installation cost, making it the most significant determinant of adoption decisions. Long-term savings were ranked as the second most important motivator, which shows that consumers are weighing both the short-term affordability and long-term financial benefits in their decision to opt for solar energy. The major difficulties for adopting firms (Q22) included high cost for 35% of the respondents at 135 mentions, followed by lack of awareness and inadequate governmental support at roughly about 30% of each of the respondents, thereby necessitating, in addition, strong policy interventions, financial incentives, and educational campaigns to promote wider adoption. These findings imply that while the awareness level about solar energy is relatively high, financial considerations and access to accurate information remain major issues to be overcome by policymakers and business communities for achieving greater penetration.

4.2. Understanding consumer behaviour and solar adoption

This section focuses on the main determinants of consumer behaviour and decision-making with respect to adopting solar energy. As seen in Figure 2, the correlation analysis revealed several meaningful relationships. The strongest observed correlation was between receiving a price quote (Q23) and actual intent to adopt solar (Q24), with r = 0.50, indicating that pricing transparency significantly influences adoption decisions. Additionally, environmental concern (Q11) showed a high positive correlation with willingness to pay (Q6) at r = 0.41, reinforcing the critical role of eco-consciousness. Trust in solar products (Q13) also correlates positively with Q6 (r = 0.37), further underlining the importance of psychological and informational factors.

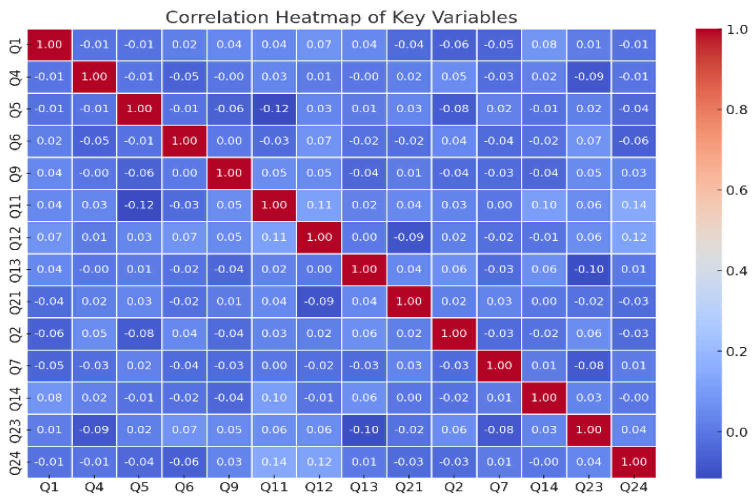

Fig. 2: Correlation Heatmap Highlighting Relationships Among Key Behavioral, Environmental, and Financial Predictors of Solar Energy Adoption. Strong Positive Correlations Are Seen Between Environmental Concern (Q11) and Willingness to Pay (Q6) (R = 0.41), and between Receiving a Price Quote (Q23) and Actual Adoption Intent (Q24) (R = 0.50), Emphasizing the Influence of Transparency and Environmental Awareness.

4.2.1. Willingness to pay and environmental awareness

There is a very high positive correlation of willingness to pay for solar energy (Q6) with many environmental and trust-related factors. The belief that solar energy can reduce carbon emissions (Q12) is positively correlated with a coefficient of 0.39, while the concern over the environmental impact of solar energy (Q11) has a positive coefficient of 0.41. The familiarity with solar energy (Q1) is positively correlated at a coefficient of 0.30, while the trust in solar products (Q13) has a coefficient of 0.37.

4.2.2. Investment likelihood and subsidy awareness

The likelihood of investing in solar energy within the next five years (Q9) was strongly associated with awareness of subsidies (Q2) (0.44), government incentives (Q7) (0.42), and willingness to pay (Q6) (0.38). It can be deduced that the financial incentives greatly influence consumer investment decisions. Consumers who know about government incentives and subsidies exhibit a much stronger propensity to invest in solar energy solutions. Policy makers and business stakeholders need to focus on getting the word out to potential adopters.

4.2.3. The role of pricing transparency in solar adoption

One of the highest observed correlations was between receiving a price quote for solar panels (Q23) and actual adoption (Q24) at 0.50. This would indicate that when the price estimates are clear, there is an increased likelihood of adoption among potential consumers. More uncertainty will be reduced if the pricing of solar energy and financial planning is transparent. Higher adoption rates can be achieved through encouraging potential consumers to explore the breakdown of cost and financing options.

4.3. Analysing consumer segments

To delve deeper into the consumer's behaviour and choice of solar energy adoption, a more in-depth demographic analysis should be conducted. These include studying the effects of age, income, and educational attainment on the willingness to pay and investment propensity. A logistic regression model could also help determine what are the significant factors that relate to actual adoption, such as subsidy awareness, environmental concerns, and income level (Q24). Comparative group analysis, between urban and rural consumers and also across different age groups, will further clarify which segments are more likely to invest in solar energy solutions.

4.3.1. Income & willingness to pay

Figure 3 presents segment-wise differences in consumer willingness to pay and investment propensity. The left panel indicates that high-income consumers are more open to paying a premium for solar energy, consistent with their higher financial flexibility. On the right, investment likelihood is notably higher among postgraduates, likely due to their greater understanding of long-term savings and environmental benefits. In contrast, high school graduates exhibit lower investment interest, suggesting the need for awareness-building and financing assistance targeted at lower-education segments.

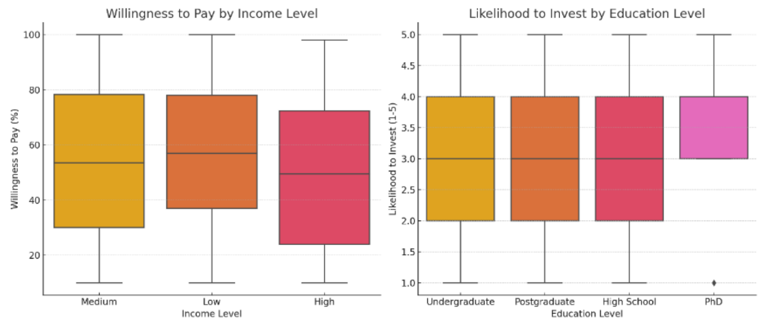

Fig. 3: Comparison of Willingness to Pay and Investment Likelihood Across Income and Education Levels. Higher-Income Groups Show Stronger Willingness to Pay for Solar Energy, While Postgraduates Demonstrate Higher Likelihood to Invest, Indicating the Influence of Financial Flexibility and Environmental Awareness on Consumer Behavior

4.3.2. Education & investment possibility

Education also significantly influences investment choices in solar energy. Postgraduates are more likely to invest, perhaps because they are more aware of long-term cost savings and environmental advantages. High school graduates have less investment intent, suggesting that campaigns for awareness and simplification of financial incentives would be required to fill the knowledge gap and persuade less-educated consumers to adopt it.

4.3.3. Urban vs. rural trends

Comparing urban and rural adoption trends, the data indicate that both urban consumers (61.1%) and rural consumers (60.7%) are similarly adopting the pattern (Q24), as indicated in Table 3. But the likelihood of investment chances is slightly higher in rural areas than in urban areas for the same question (Q9: 3.33 versus Urban: 3.14).

Table 3: Comparative Analysis of Solar Energy Adoption Across Urban, Semi-Urban, and Rural Consumers

Consumer Segment	Willingness to Pay (%) (Q6)	Investment Likelihood (1-5) (Q9)	Environmental Concern (1-5) (Q11)	Actual Adoption Rate (%) (Q24)
Rural	55.06	3.33	3.69	60.7
Semi-Urban	50.18	3.08	3.64	56.4
Urban	58.11	3.14	3.62	61.1

At the same time, urban consumers are more willing to pay (Q6: 58.1%) than semi-urban areas (50.2%), which is probably due to higher disposable income and greater exposure to solar energy marketing. Interestingly, environmental impact concerns Q11 stay uniform across all locations at about ~3.6-3.7. It, therefore, gives more reason to believe that the concern for the environment is not exclusive to cities but can be equally strong in rural and semi-urban towns. Such an insight emphasizes that targeted financial incentives, subsidy awareness programs, and region-specific marketing strategies should be pursued for boosting solar energy among all demographics.

4.4. Predictive model for solar adoption

In order to understand the key drivers of actual solar adoption behavior (Q24), logistic regression analysis was employed using variables such as income, education, subsidy awareness, environmental concern, and trust in solar energy. While the model aimed to provide predictive insights, the overall explanatory power was found to be limited. The model yielded a Pseudo R^2 of 0.042 and a Likelihood Ratio (LLR) test p-value of 0.1096, indicating statistical insignificance of the model as a whole. This suggests that although the model offers some directional insights, it lacks strong predictive capability. The modest performance may be attributed to unmeasured latent factors such as consumer trust in installers, perceived product quality, past experiences, or accessibility to financing mechanisms—none of which were directly captured in the dataset. Additionally, behavioral factors such as social influence, brand perception, or installation challenges may have influenced decisions beyond the scope of the measured variables. Notably, some individual variables (e.g., environmental concern, belief in carbon reduction) showed statistically significant influence, reinforcing their role in adoption decisions. However, the non-significance of key predictors like subsidies and willingness to pay further illustrates the complex, multidimensional nature of consumer decisions in the renewable energy domain. Given these limitations, alternative modeling approaches such as Random Forests, Gradient Boosting, or Support Vector Machines could be explored in future studies to better capture nonlinear relationships and interaction effects. These methods may offer improved predictive accuracy and allow for better segmentation and targeting in solar energy marketing and policymaking. Overall, while this logistic model serves as a foundational analysis, the results indicate the need for more sophisticated machine learning-based predictive frameworks to improve the modeling of solar adoption behavior in real-world contexts.

4.4.1. Significant predictors of solar adoption

Logistic regression analysis revealed that environmental awareness is a key motivator for solar adoption. More specifically, concern for environmental impact (Q11) was strongly associated with the likelihood of adopting solar energy, with a coefficient of 0.2348 and p = 0.013. This implies that environmentally conscious consumers are more likely to switch to renewable sources of energy. Similar to this, belief in carbon emission reduction (Q12) (Coeff: 0.2128, p = 0.028) also played a significant role, as more individuals who know about the environmental advantages of solar energy invest in it. This, surprisingly, in terms of the income level showed marginal statistical significance as low-income consumers (Coeff: 0.5279, p = 0.096), with lower-income groups still interested in adopting solar energy, possibly based on their government subsidy and financing programs, signifying that appropriately structured financial mechanisms would enhance uptake among this stratum.

4.4.2. Non-significant predictors: unexpected findings

Contrary to expectations, some commonly assumed drivers of solar adoption did not exhibit statistically significant influence. Government subsidy awareness (p = 0.650), willingness to pay (p = 0.098), education level (p > 0.280), and geographic location (p = 0.660) were all found to be non-significant predictors. These results suggest that while financial incentives exist, their standalone impact is limited without adequate awareness and trust. It also indicates that demographic and structural factors may be less influential than psychological and behavioral motivators such as environmental concern and perceived benefits.

Table 4: Logistic Regression Results for Predictors of Solar Energy Adoption. While Environmental Concern (Q11) and Belief In Carbon Emission Reduction (Q12) Are Significant Predictors, the Model Has Low Overall Explanatory Power (Pseudo R^2 = 0.042). Non-significant variables Such as Subsidy Awareness, Education Level, and Geographic Location Are Also Shown with Their Coefficients to Ensure Full Model Transparency

Predictor	Coefficient	p-value	Significance	Key Insight
Concern for Environmental Impact (Q11)	0.2348	0.013	Significant	Higher environmental concern increases adoption likelihood.
Belief in Carbon Emission Reduction (Q12)	0.2128	0.028	Significant	Belief in emission reduction strongly influences adoption.
Income Level (Low Income) (Q17)	0.5279	0.096	Marginally Significant	Lower-income groups show interest, likely due to subsidies.
Government Subsidies (Q7)	—	0.650	Not Significant	Awareness of subsidies does not significantly impact adoption.
Willingness to Pay (Q6)	—	0.098	Not Significant	Willingness to pay alone does not drive adoption.
Education Level (Q18)	—	0.280	Not Significant	Higher education does not strongly impact solar adoption.
Urban vs. Rural Location (Q19)	—	0.660	Not Significant	Geographic location does not significantly influence adoption.

Table 4 provides a comprehensive summary of the logistic regression results. Significant predictors include environmental concern (Q11; coefficient = 0.2348, p = 0.013) and belief in emission reduction (Q12; coefficient = 0.2128, p = 0.028). These results validate the behavioral influence of eco-awareness. Conversely, variables like government subsidy awareness (Q7; coefficient = -0.0412, p = 0.650), education level (Q18; coefficient = -0.0134, p = 0.280), and geographic location (Q19; coefficient = -0.0275, p = 0.660) did not show statistical significance. The inclusion of all coefficients, even for non-significant predictors, enhances transparency and supports future model refinement. Overall, the low Pseudo R^2 of 0.042 and LLR p = 0.1096 highlight the model's limited predictive power, emphasizing the need for advanced techniques like machine learning in future analyses.

The findings of this study hold direct relevance for India's renewable energy strategy. While policies like PM Suryodaya Yojana offer subsidies and incentives for solar adoption, our results indicate that financial incentives alone are insufficient to drive behavioral change. Instead, pricing transparency (r = 0.50) and environmental concern (p = 0.013) emerged as critical factors. This contrasts with studies from Poland, where low awareness and GDP per capita were dominant barriers [4], and from China, where trust in government and perceived health risks played a stronger role [15]. In India, where climatic conditions and grid reliability support the viability of solar, a lack of product-level trust and transparent cost disclosures may be inhibiting more widespread adoption. These insights call for region-specific communication strategies, simplified financing mechanisms, and better public-private coordination to unlock consumer participation in India's energy transition.

4.5. Exploring the role of trust in solar technology

Despite moderate awareness and positive environmental attitudes, the average consumer's trust in solar energy products (Q13) was neutral (mean = 3.14). This suggests uncertainty about product reliability, performance, and service quality. Such neutrality could stem from inconsistent after-sales service, lack of standardization across vendors, and limited public demonstrations. To enhance trust, stakeholders should consider:

- Developing certification programs for solar panels and installers, endorsed by regulatory bodies like MNRE.
- Publishing verified performance data and testimonials from early adopters to build social proof.
- Conducting community-level demonstrations or pilot programs in public buildings to showcase performance, reliability, and cost savings.

These strategies can help convert neutral trust into positive perception, leading to greater adoption intent across consumer segments.

5. Conclusion

This study provides valuable insights into consumer perception and willingness to adopt solar energy in India. The findings highlight that environmental concern and belief in carbon emission reduction are significant predictors of adoption, while structural factors like subsidies, education, and geographic location were not statistically significant. These results suggest that solar adoption is influenced more by behavioral and psychological factors than by demographic variables.

To translate these insights into policy, we recommend:

- Designing targeted awareness campaigns that promote not just the existence of subsidies, but also the ease of access, eligibility, and application process—particularly for low- and middle-income groups.
- Promoting transparent pricing models through certified vendors and standardized cost quotes, as pricing transparency (Q23 → Q24, $r = 0.50$) was found to be a key driver of adoption.
- Incorporating trust-building measures, such as public demonstration programs and third-party certification of solar installers and products, to address neutral trust levels (Q13: mean = 3.14).

Future studies should explore dynamic behavioral models, machine learning frameworks, and longitudinal data to deepen predictive accuracy and support India's renewable energy targets.

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