Assessment of Adoption and Satisfaction of Consumer Towards Renewable Energy Sources: A Study of Solar Panels

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Abstract: Environmental concerns and technological breakthroughs have greatly accelerated the adoption of solar energy as a renewable energy source in recent years. This study explores the economic, environmental, and social aspects that influence consumer decisions in relation to the adoption of solar panels by drawing on a thorough analysis of the body of empirical research and current literature. Through cost-benefit assessments, financial incentives, and the effect on energy bills, the economic element of the adoption of solar panels is investigated. Environmental factors include reducing greenhouse gas emissions and the ecological impact of producing and disposing of solar panels. This study explores the influence of social factors, including peer pressure, neighborhood initiatives, and governmental regulations, on whether solar panel adoption is encouraged or discouraged. Additionally, this research explores how consumer behavior is changing in reaction to the deployment of solar panels. This research contributes to a thorough knowledge of the complex relationship between the adoption of solar panels and consumer behavior by combining these numerous factors.

Keywords : ***Solar panels , Consumer behavior, Technology adoption***

INTRODUCTION

As the world grapples with the imperatives of curbing carbon emissions and mitigating climate change, the adoption of solar panels for energy generation has gained significant attention. Briguglio & Formosa (2017) study that the prevalence of younger households, higher incomes, home ownership, and unshared roof space leads to increased adoption rates. In this context, understanding consumer perception regarding the adoption of solar panels becomes not only relevant but imperative in shaping the trajectory of this transformative energy transition. The transition to solar power is more than just a technical transformation; it represents a shift in mindset towards embracing sustainable and cleaner energy alternatives. As consumers become increasingly cognizant of the environmental repercussions of fossil fuel consumption, the appeal of solar panels lies not only in their potential to reduce electricity bills but also in their capacity to contribute to a greener future.

Overholm, (2015) Solar TPO business models, which involve third-party owners (TPO) firms installing, financing, and managing solar panels, can increase market demand by removing barriers like technology risk and financing needs. Al-Saadi et.al.,(2017) The increasing installation of solar panels on Australian rooftops has led to increased uncertainty about grid-connected solar panels. Social influences, including peer recommendations, community norms, and the influence of opinion leaders, further contribute to the intricate mosaic of consumer perception surrounding solar panels. The adoption of solar technology can be a reflection of personal values and identity, influenced by the desire to align with emerging sustainable trends and make a positive social statement.

Consumer perception

Consumer perception, a cornerstone of consumer behavior studies, delves into how individuals interpret and make sense of the world around them, particularly in relation to products, services, and brands. Its evolution over time has been influenced by shifts in theoretical paradigms, advancements in research methodologies, and changes in societal and technological landscapes.

Objectives of the study

This study is titled " CONSUMER PERCEPTION TOWARDS ADOPTION OF SOLAR PANELS." This study's main purpose is to determine the " how consumers perceive solar panels use, ease of use, acceptance, complexity, compatibility, risks, satisfactions and barriers. The following objectives were developed:

- To analyze consumer perception in relation to perceived use.
- To analyze consumer perception in relation to perceived ease of use.
- To analyze consumer perception in relation to user acceptance.
- To analyze consumer perception in relation to complexity.
- To analyze consumer perception in relation to compatability
- To analyze consumer perception in relation to their satisfaction level.

LITERATURE REVIEW

Claudy et.al. (2013) explain how consumers feel about the adoption of renewable energy systems, researchers and marketers should include mediating concepts such as (i) reasons for adoption, (ii) reasons against adoption, and (iii) attitudes toward a technology.
Bauner & Crago (2015) determine optimal adoption times, critical values of discounted benefits, and adoption rates over time for Massachusetts solar PV investments using a simulation model.
Sesmero et.al. (2016) states that pricing can either improve or degrade the economics of PV systems. In addition, an increase in the sensitivity of electricity demand to its price reduces the efficacy of pricing in the absence of net metering, but has no other effect.
Bao et.al. (2017) studies a case study of residential solar panels, the influence of the aesthetic appeal of renewable energy systems on consumer preference is investigated.
Chesser et.al. (2018) studies the need for stakeholders to consider this issue when formulating future energy policies to ensure that the adoption of solar PV is supported in a sustainable manner and that non-adopters are not penalized with increased electricity rates.
Pan et.al. (2019) demonstrates a prompt investment decision for each scenario. A constant FIT will increase the producer's return on investment in constructing a solar power facility. Export is

the best option in situations where the return on investment is minimal. The paper concludes with a sensitivity analysis and can serve as a toolkit for solar panel manufacturers and a reference for policymakers evaluating the impact of policy uncertainties.
Priessner & Hampl (2020) studies different segments have distinct product preferences, highlighting the need for individualized bundle packages. In addition, we demonstrate that policy incentives are more effective when product bundles are labeled with price tags that already reflect subsidies. Gillingham & Bollinger (2021) study suggests that the program provided economies of scale and decreased consumer acquisition costs, resulting in inexpensive emission reductions. Zander (2021) studies median FiT required for people to acquire solar panels for the first time was 14.40 cents per kilowatt-hour, according to a contingent valuation (95% confidence interval: 10.74–25.40 cents).

Ardila et.al. (2022) evidence-based best practices for solar irrigation solutions at the farm level, so that the dissemination of this revolutionary technology, in addition to contributing to the advancement of the energy sector, plays a crucial role in propelling us toward establishing a more equitable and sustainable world.
Kunreuther (2022) studies adoption of solar panels is encouraged by a behavioral risk assessment that addresses biases in conjunction with short-term economic incentives, social influences, and regulation. Sovacool et.al. (2022) gave a framework which facilitates the identification of multiple, often interconnected inequities, but also indicates how to make the adoption of solar energy more sustainable and equitable, with direct implications for solar business practices (and supply chains) as well as energy and climate policy.
Aydin et.al. (2023) studies households shift their electricity consumption to times when solar electricity production is highest. The solar PV rebound effect exhibits heterogeneity across time and production level, with greater rebound effects during seasons with greater solar irradiance.
Lemay et.al. (2023) reveals that rooftop solar adoption, defined as the number of buildings with extant photovoltaic (PV) installations divided by the total number of eligible buildings, was low (mean of 0.93 percent across 10,417 U.S. ZIP codes).

Research Methodology

This chapter details the research technique, methodology, design, instrument development, sampling strategy, and data collecting. Using a study method of analysis, the influence of Artificial Intelligence on consumers is analyzed.

Research Design

According to Rojon & Saunders (2012), "Research design is the general plan of research that helps obtain answers to research questions." Yet, the research design is comparable to the overall plan, which describes how the study will be conducted. Thus, it must be straightforward, well-defined, and expressed in the manner. In the present research Exploratory and cross-sectional descriptive approaches are used. Exploratory research is a (Creswell & Plano-Clark, 2007). "two stage design which involves qualitative data being used as a basis on which to build and explain quantitative data gathering process". **Data Collection**
There are 2 types of data collection sources. Primary data and Secondary data (Kothari, 1985)

Primary data: ***Questionnaire and Personal observation.***

Secondary data: ***Articles from journals, newspapers and Internet***.

1. **Sampling design**

It is a strategy that concludes a whole people based on the findings of a sample that comprises just a small portion of the entire population (Banerjee et al., 2010; Cavana et al., 2001). Specifically, this procedure occurs prior to data collection. The researcher must select a sample design that is trustworthy and suitable for the investigation. Hence, a thorough discussion of the sampling design decision is required. In this study, sampling design used is ***non-probability convenience sampling.*** Non-probability sampling is (Kothari) that sampling procedure which does not afford any basis for estimating the probability that each item in the population has of being included in the sample.

Sample size

For the present study, data was collected through a questionnaire(517)distributed to consumers of different demographics ***through post and google forms*** and finally we received a responses from respondents which are used for the further analysis in the study.

2. **Tools and techniques for data analysis.**
   The statistical tools used in the study are ***One-way ANOVA***, ***Correlation analysis, Regression analysis*** and ***Student's t-test*** (also called T test) is used to compare the means between two groups and there is no need of multiple comparisons as unique P value is observed (William Sealy Gosset, 1908).
3. **Software tools for data analysis**.
   Software for data analysis is necessary for a clear perspective and reliable results and conclusions. ***IBM SPSS*** statistical software suite was utilized for data management, advanced analytics, multivariate analysis, business intelligence and ***Microsoft Excel*** is a spreadsheet application designed for Windows, macOS, Android, iOS, and iPadOS by Microsoft.

Table: 1 Source of awareness

Source of awareness

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Advertisement	135	26.1	26.1	26.1
	Government departments	249	48.2	48.2	74.3
	Friends/ Family	133	25.7	25.7	100.0
	Total	517	100.0	100.0	

Out of 517 respondents, 135 (26.1%) respondents are aware through advertisements and only 133 (25.7%) respondents are aware through friends/ family.

Table: 2 use of solar panel.

use of solar panel

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Yes	242	46.8	46.8	46.8
	No	275	53.2	53.2	100.0
	Total	517	100.0	100.0	

Out of 517 respondents, 275 (53.2%) respondents are saying that they are not using solar panels till date and 242 (46.8%) respondents are saying that they are already using solar panels.

Table 3- The below figure shows the value of Cronbach's alpha, Composite reliability (rho_a), Composite reliability (rho_c) & Average variance extracted (AVE) that states the reliability and validity of the model.

	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)
BI	0.859	0.868	0.9	0.647
CL	0.875	0.88	0.909	0.666
CS	0.886	0.888	0.917	0.69
CX	0.885	0.893	0.916	0.689
PEU	0.865	0.869	0.903	0.652
PR	0.836	0.843	0.885	0.608
PU	0.852	0.873	0.898	0.646

Table 4- It shows the value of HTMT, which is used for assessing discriminate validity.

	Heterotrait-monotrait ratio (HTMT)
CL <-> BI	0.65
CS <-> BI	0.689
CS <-> CL	0.878
CX <-> BI	0.662
CX <-> CL	1.009
CX <-> CS	0.933
PEU <-> BI	0.691
PEU <-> CL	1.068
PEU <-> CS	0.932
PEU <-> CX	1.025
PR <-> BI	0.932
PR <-> CL	0.797
PR <-> CS	0.891
PR <-> CX	0.775
PR <-> PEU	0.832
PU <-> BI	0.716
PU <-> CL	1.081
PU <-> CS	0.929
PU <-> CX	1.088
PU <-> PEU	1.116
PU <-> PR	0.814

Results: Structural Model Assessment

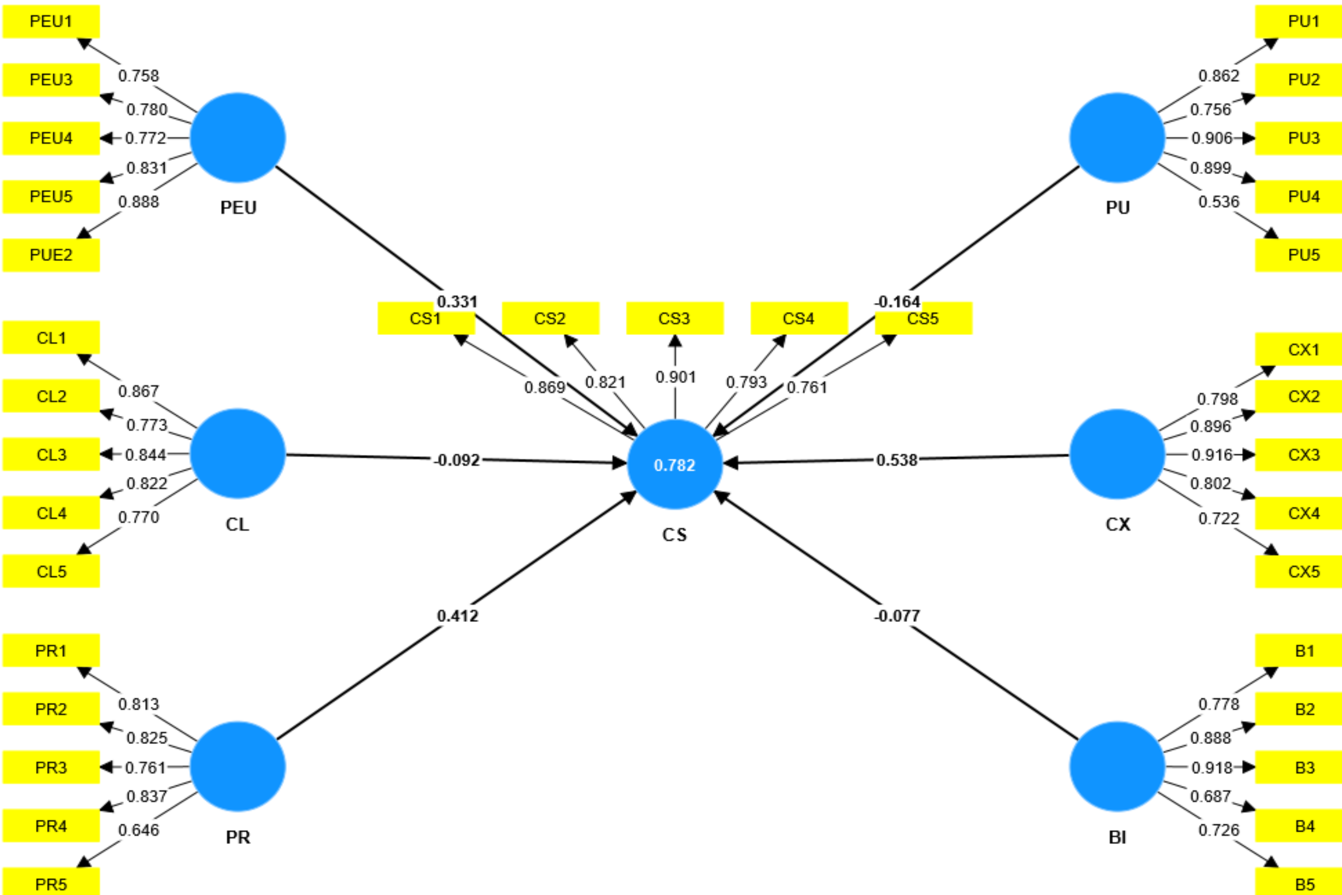

Figure 1: PLS-SEM Aggregate Model

After examining and confirming the reliability and validity of the measurement model, the study assesses the structural model. Figure 1 presents the structural model, which shows the relationship between the latent constructs (Hair et al., 2017). There is no multicollinearity because the VIF for each construct in the structural model is less than 5, which is a sign.

Next, the study analyses the path coefficients to explore the strength and direction of the relationship among the constructs. The study follows the recommendation by Hair et al. (2021) and performs bootstrapping (with 5,000 resamples) to test the statistical significance of each path coefficient.

Table 5- Path Coefficients by Bootstrapping (5000 resamples)

Path Coefficients by Bootstrapping (5000 resamples)					
	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values
BI -> CS	-0.077	-0.076	0.04	1.918	0.055
CL -> CS	-0.092	-0.089	0.066	1.402	0.161
CX -> CS	0.538	0.542	0.076	7.054	0
PEU -> CS	0.331	0.332	0.074	4.477	0
PR -> CS	0.412	0.406	0.074	5.59	0
PU -> CS	-0.164	-0.168	0.101	1.629	0.103

By comparing each path coefficient to the standard deviation, the T statistics (O/STDEV) determine the relevance of each path coefficient. The association between the predictor and the outcome variable is thought to be stronger when the T statistic is higher. In this instance, the path from CX to CS has the highest T statistic (7.054), suggesting a highly significant association. PR -> CS comes next (5.59), PEU -> CS (4.477), BI -> CS (1.918), CL -> CS (1.402), and PU -> CS (1.629) are all highly significant relationships. The P values—which come last—display the significance level of each path coefficient. It is suggested that there may be a statistically significant link between the predictor and the outcome variable if the P value is less than 0.05, which is generally regarded as the threshold for statistical significance. Notably, the route coefficients for CX -> CS and PEU -> CS have P values of 0, indicating a highly significant association, while the others have P values marginally higher than 0.05.

Conclusion

Firstly, results of t-test, one-way ANOVA and correlation analysis made it evident that the perceived use of solar panel for consumers is high as sustainable energy sources, driven by environmental concerns and the need for energy security, has significantly influenced consumer attitudes towards solar panel adoption. Compatibility of solar panel has increased and complexity has reduced during the recent years and this has resulted into increased customer satisfaction. Perceived risks have also decreased due to increase in consumer awareness and elimination of fear of unknown.

Furthermore, this thesis has highlighted the importance of information and awareness in shaping consumer perceptions. Education campaigns and peer-to-peer communication have played a crucial role in dispelling misconceptions, raising awareness about the benefits of solar panels, and instilling confidence in potential adopters.

Additionally, the role of social norms and cultural factors cannot be underestimated. As solar panel adoption becomes more commonplace and socially endorsed, it further encourages others to follow suit, creating a positive feedback loop for widespread adoption.

Limitation and scope of future research

One of the primary limitations of this study is the sample size and demographic representation. The research may have been conducted in a specific region or with a particular demographic group, which may not be fully representative of the diverse consumer population.

The research may have been conducted over a limited timeframe, which could impact the accuracy of long-term perceptions and attitudes towards solar panel adoption. Longitudinal studies that track consumer perceptions over an extended period would provide a more comprehensive understanding of how attitudes evolve over time.

Like any survey-based research, the study might be susceptible to self-report bias, where respondents provide socially desirable responses or may not accurately recall their true experiences or beliefs. Employing complementary research methods, such as observational studies or in-depth interviews, could help triangulate the data and minimize the impact of self-report bias.

Solar panel technology is rapidly evolving, and newer innovations may impact consumer perceptions and adoption. The research might not fully account for the influence of cutting-edge technologies or emerging trends. Constant updates and reassessment of consumer perceptions would be necessary to capture the evolving landscape accurately.

Future research could conduct comparative studies between different regions or countries to explore the cultural and regulatory influences on consumer perception towards solar panel adoption. Understanding how cultural norms and policy variations impact consumer behavior would be valuable for policymakers and industry stakeholders.

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