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Cost-Benefit Dynamics and Behavioral Barriers to Solar Energy Adoption: Evidence from Structural Equation Modeling in Urban India

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KEYWORDS

Solar Energy Adoption, Structural Equation Modeling, Socio-Economic Impact, Affordability, Policy Incentives, Urban Sustainability.

ABSTRACT

This research explores solar energy uptake drivers and socio-economic impacts in low-income neighborhoods in Bengaluru, India. Employing Structural Equation Modeling (SEM) and Exploratory Factor Analysis (EFA), the results identify affordability, policy incentives, awareness, and infrastructure preparedness as the most important determinants. SEM analysis reveals that usage of solar ($\beta = 0.33$, $p < 0.001$) is the most predictive of socio-economic impact, followed by perceived savings ($\beta = 0.30$, $p < 0.001$), perception of environmental benefit ($\beta = 0.28$, $p < 0.001$), awareness ($\beta = 0.27$, $p < 0.001$), and government incentives ($\beta = 0.25$, $p = 0.001$). Enablers identified are affordability and incentives, and adoption motivation is mediated by awareness and trust. Placed in the Technology Acceptance Model and Diffusion of Innovation Theory, the research provides a comprehensive framework that balances institutional and user-level dynamics. Though cross-sectional constraints indicate the necessity for longitudinal work, the research provides policy-relevant insights calling for fiscal incentives, outreach targeting communities, and regulatory incentives to aggregate solar penetration across underserved urban communities.

1. INTRODUCTION

The worldwide shift towards renewable energy has increased emphasis on solar energy as a green, renewable, and decentralized energy solution to city electricity issues. Solar systems installed on rooftops, especially, have promising potential to limit greenhouse gas emissions, improve energy security, and mitigate grid strain in densely populated urban areas (IRENA, 2021). In India, the Jawaharlal Nehru National Solar Mission has built on this momentum by establishing aggressive goals to increase solar capacity and decrease fossil fuel dependence (MNRE, 2022).

Bengaluru, a fast-developing metropolitan center, is a classic example of the necessity for such a shift with high energy requirements, regular outages, and growing environmental pressure (Garg et al., 2020). Although technologically feasible, rooftop solar solutions depend on socio-economic considerations such as perceptions of costs, level of environmental awareness, trust in technology, and government incentive responsiveness (Bhattacharyya & Ohiare, 2012; Yadav & Pathak, 2022). Regulatory hurdles, high capital expenditure, and shortage of access to finance, however, remain to limit the uptake (IRENA, 2021).

This research examines household-level adoption patterns, levels of awareness, and perceived socio-economic effects of solar energy in Bengaluru. Utilizing Exploratory Factor Analysis (EFA) and Structural Equation Modeling (SEM), it examines the contribution of mitigation strategies towards overcoming adoption constraints and offers guidance for inclusive urban energy policy

2. REVIEW OF LITERATURE

Introduction

Urban sustainability has become a key concern for rapidly developing cities throughout the Global South, where fast-growing populations and infrastructure strain threaten environmental resilience. Bengaluru, the IT center of India, presents a fascinating example to consider how the uptake of solar energy promotes sustainable urbanization. As home electricity consumption is expected to double by 2040 (Quraishi & Ahmed, 2019), integrating renewable energy is not just an environmental priority but a socioeconomic imperative. Drawing on empirical literature and policy reflections, this review synthesizes solar energy's potential in defining Bengaluru's sustainable urban futures.

Sustainable Urban Living and Solar Energy: A Conceptual Framework

Sustainable city living means reducing environmental impacts, enhancing quality of life, and providing fair access to resources (Kalfas et al., 2023). Solar energy directly supports these objectives by providing decentralized, clean, and lower-cost energy. For Bengaluru, energy-consuming lifestyles, growing middle-class residences, and an overburdened electricity grid make solar uptake both a prospect and a challenge (Bhattacharyya, 2014; Ramachandra et al., 2020).

Policy and Governance Environment

Urban Renewable Energy Planning

India's National Solar Mission has established a strong basis for solar energy deployment, but its success in cities such as Bengaluru is critically dependent on localized implementation. The Karnataka Solar Policy (2014–2021), net metering rules, and focused subsidies were formulated to promote residential rooftop solar adoption. Nonetheless, uneven implementation by city authorities like the Bruhat Bengaluru Mahanagara Palike (BBMP) and weak inter-agency coordination have slowed city-wide implementation (Ganesan et al., 2019). In contrast to rural solar take-up naturally incentivized by central schemes, urban rollouts of solar need decentralized management, neighborhood planning, and increased civic participation (Narasimhan et al., 2018).

Policy Outcomes: What the Data Reveals

Even with the availability of incentives, empirical evidence indicates that rooftop solar adoption is still below set targets, particularly in poorer neighborhoods (Sukumaran & Sudhakar, 2017). Administrative complexity and a lack of proper dissemination of subsidy programs often hinder eligible residents from taking advantage of the benefits (Sharma et al., 2021). Therefore, the policy does not achieve equity-based objectives, confirming the need for focused communication, streamlined procedures, and monitoring systems.

Infrastructure and Design Issues of Urban Solar Integration

The built-up area in Bengaluru poses major challenges to the deployment of solar. Legacy buildings have challenges like shading, lack of rooftop space, and old zoning regulations (Ramachandra & Shwetmala, 2020). Research indicates that solar potential is highly differentiated between wards, making micro-level urban energy mapping necessary (Kulkarni & Anil, 2018). In addition, Bengaluru's current grid is not strong on voltage regulation and intelligent load-balancing measures in high-solar-density areas, which hampers distributed energy integration (Bhattacharyya et al., 2019). Resolving these issues is imperative to scale solar adoption and provide a fair, efficient energy transition.

Potential for Rooftop Solar in Bengaluru

Bengaluru's rooftop solar potential is highly variable over its urban space. High-potential areas like Whitefield, Electronic City, and Yelahanka have low shading, large rooftop areas, and suitable building orientations, which are well-suited for large-scale solar installations. Moderate-potential areas like Jayanagar and Indiranagar have limitations such as periodic shading or smaller rooftops but are still suitable for focused solar projects with optimized designs. Conversely, low-potential areas like Chickpet and Shivajinagar - characterized by high-density development, chronic shading, and poor rooftop availability are challenging for solar deployment, with innovative solutions (e.g., community solar or vertical PV systems) required to tap their residual potential. Such spatial variations call for ward-level solar policies and geospatial planning to enhance Bengaluru's renewable energy transition (Energetica India).

EMPIRICAL GAPS AND DIRECTIONS FOR FUTURE RESEARCH

Although solar energy deployment in urban India, specifically within cities such as Bengaluru, has received growing interest, some empirical research gaps persist. One such critical one is the absence of geospatial analysis for identifying fine-grained adoption patterns and generation potential at the ward or neighborhood level. Mapping this is necessary in order to inform focused policy interventions and maximize solar investments in varied urban geographies. Also, there exists minimal longitudinal evaluation of how regular solar energy application alters household culture, energy conserving practices, and larger objectives such as decreased carbon emissions and city climate adaptability.

One other under-investigated field is the position of institutional alignment in influencing acceptance outcomes. The engagement between regulatory agencies like the Bruhat Bengaluru Mahanagara Palike (BBMP), Bangalore Electricity

Supply Company (BESCOM), and Real Estate Regulatory Authority (RERA) needs closer examination to determine if existing governance systems assist or hamper efficient solar deployment. Lastly, justice and equity issues are typically not accounted for in solar uptake research. There is an urgent need to empirically examine which parts of the population gain most from subsidies and installation schemes, and which ones are still left behind. Knowing these inequalities is crucial for the design of inclusive energy transitions that leave no one behind.

Solar energy is transformative in fulfilling sustainable urban existence in Bengaluru. Yet, more than technology is needed to realize this transformation - effective governance, inclusive funding, focused awareness, and coherent urban planning. Empirical evidence is key in revealing spatial tendencies, policy effects, and social processes that are molding solar energy's urban future. This review therefore provides the basis for the current empirical research, which examines actual-world determinants and hindrances to solar energy utilization throughout Bengaluru's varied urban environment.

3. METHODOLOGY

Research Design

The research utilized a quantitative, cross-sectional survey design to examine the socio-economic effects of solar energy adoption among Bengaluru residents. The aim was to identify how awareness, perceived benefits, and government incentives support the impact of household-level solar adoption and its wider ramifications.

Conceptual Framework

In this research, a conceptual model was framed to investigate the interrelationship among awareness, education, and solar energy adoption motivation in Bengaluru. The model postulates some direct and indirect relationships, as shown in Figure 1. This framework is used to frame the SEM model, which is pivotal to the data collection and analysis plan.

The drivers of solar energy adoption motivation (DV) are explored in this study using four major independent variables (IVs): (1) Awareness of solar energy benefits; (2) Government policy and incentives; (3) Economic viability (e.g., cost savings, subsidies); and (4) Infrastructure readiness (e.g., grid stability, rooftop space).

Hypotheses Development

The independent variables and adoption relationship are hypothesized to be mediated by education level/access to informational resources, as knowledge gaps can impede uptake even with supportive policies or infrastructure.

With reference to the theoretical underpinnings elucidated in the earlier sections, the following hypotheses are examined:

H1: Awareness → Adoption Motivation

H2: Awareness → Education

H3: Education → Adoption Motivation

H4: Education mediates the relationship between Awareness and Adoption Motivation

H5: Economic Viability → Adoption Motivation

H6: Government Policy → Awareness

H7: Infrastructure Readiness → Adoption Motivation

These hypotheses serve as the foundation of the SEM model applied in this study where the path relationships between these variables are examined in order to determine the drivers of solar energy adoption motivation.

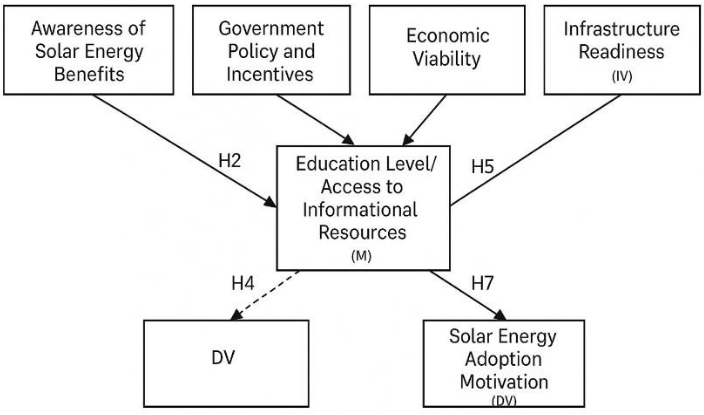

Figure 1: Conceptual model outlining the hypothesized relationships among awareness, education, and solar adoption motivation.

Note: IV = Independent Variable; DV = Dependent Variable; and M = Mediator.

Sampling and Data Collection

Purposely sampling was employed to obtain varying response types of households from different wards in Bengaluru. The sampling was spread across multiple wards in Bengaluru with varying rates of solar energy uptake. There were 250 valid responses obtained for analysis. Out of the 250 responses, 160 responses (64%) were obtained from face-to-face surveys conducted through trained field researchers to give assurance on data quality and help in clarifications. The other 90 responses (36%) were gathered online, via structured Google Forms distributed via resident welfare associations and sustainability networks. This mixed-mode strategy facilitated more extensive coverage across socio-economic strata and representation from both digitally literate and conventionally surveyed populations.

Measurement of Variables

The research assessed primary constructs on a five-point Likert scale (1 = Low/Disagree to 5 = High/Strongly Agree). Variables comprised:

- Awareness of Solar Energy
- Extent of Solar Use
- Perceived Cost Savings
- Environmental Benefit Perception
- Support for Government Incentives
- Socio-Economic Impact

Information regarding demographics like monthly income (in INR) and family size was also gathered.

Data Analysis Methods

Descriptive statistics were calculated to present the profile of respondents and main variables. Cronbach's alpha was used to carry out reliability analysis, and Exploratory Factor Analysis (EFA) with Varimax rotation was utilized to cross-validate construct dimensions. Kaiser-Meyer-Olkin (KMO) and Bartlett's Test of Sphericity were employed to test data applicability for factor analysis.

For inferential analysis, Structural Equation Modeling (SEM) was conducted to examine hypothesized relationships between constructs, model fit indices, and mediation effects. Fixed and Random Effects Models were also estimated to account for unobserved heterogeneity and test robustness.

Socio-Economic Profile and Descriptive Insights of Respondents

The information contained in Tables 1 and 2 sheds important contextual light on the socio-economic profile of respondents and household-level effects of solar energy adoption. Table 1 presents primary descriptive statistics for income, savings, and quality-of-life variables. Average monthly household income stands at ₹51,600 (SD = ₹15,120), indicating high economic diversity among interviewed households. Interestingly, a mean electricity bill saving of ₹4,650 per month is reported by households, reflecting measurable economic gains due to rooftop solar adoption. As developmental impacts, a mean 3.25 jobs are tied to each project of solar installation, highlighting the scope for in situ employment generation. Educational gain (mean index = 0.68) and health benefit (mean index = 0.73) imply wider socio-economic spillover impacts. Community satisfaction is great (mean = 4.10 on a 5-point scale), reflecting strong user acceptance and perceived usefulness of solar energy systems.

Table 2 presents the demographic and occupational characteristics of respondents. The sample has gender balance (56% male, 44% female) with a peak in the 31–45 age group (47.5%), reflecting economically active households. A high percentage (52.5%) have graduate or postgraduate education, indicating relatively high educational levels. Respondents are occupied mainly in agriculture (29%) and services (23.5%), which reflects the semi-urban and rural nature of the sample. Geographically, 55% are in rural areas and 45% in semi-urban locations. This population diversity increases the generalizability of the study and offers a strong foundation to examine the socio-economic effects of solar energy uptake across various segments of households.

Table 1: Descriptive Statistics of Variables

Variable	Mean	Standard Deviation	Minimum	Maximum
Household Income (INR/month)	₹51,600	₹15,120	₹20,000	₹1,25,000
Electricity Cost Savings (INR/month)	₹4,650	₹1,680	₹800	₹8,500

Employment Generation (jobs/project)	3.25	1.12	1	6
Education Improvement Index (0–1 scale)	0.68	0.15	0.30	0.95
Health Benefit Index (0–1 scale)	0.73	0.18	0.35	0.96
Awareness Level (1–5 scale)	3.42	0.84	1	5
Community Satisfaction (1–5 scale)	4.10	0.72	2	5

Source: Author's compilation.

Table 2: Summary of Respondent Distribution and Profile

Category	Sub-category	Frequency (n)	Percentage (%)
Gender	Male	112	56%
Female	88	44%	
Age Group	18–30 years	45	22.5%
	31–45 years	95	47.5%
	46–60 years	42	21%
	Above 60 years	18	9%
Education Level	Primary	35	17.5%
	Secondary	60	30%
	Graduate	72	36%
	Postgraduate and above	33	16.5%
Occupation	Agriculture	58	29%
	Service	47	23.5%
	Business	35	17.5%
	Homemaker	26	13%
	Others	34	17%
Location	Rural	110	55%
	Semi-urban	90	45%

Source: Author's compilation.

STRUCTURAL EQUATION MODELING (SEM) AND RESULTS

Structural Equation Modeling (SEM) Model Specification

The Structural Equation Model (SEM) employed in this research seeks to investigate the socio-economic effects of solar energy adoption in regional towns by determining the interrelations among the most important latent constructs. The model comprises both exogenous and endogenous variables grounded in theoretical foundations and empirical findings.

Latent Constructs, Indicators, and Hypothesized Structural Relationships

This research applies a solid Structural Equation Modeling (SEM) approach in order to estimate the socio-economic effects of solar energy uptake, applying five theoretically developed and empirically tested latent constructs. Table 3 reports the constructs and their respective observed variables, which are each measured on a Likert scale. The initial construct, Awareness (AW), identifies the level of public awareness about solar energy based on three indicators: awareness of government programs (AW1), knowledge of solar advantages (AW2), and possession of information sources (AW3). This construct serves as a building block for solar adoption attitudes. Affordability (AF), the second latent variable, is measured through household ability for initial outlay (AF1), perception of system price (AF2), and willingness to pay (AF3). These are economic obstacles often mentioned in the literature on the energy transition.

The third construct, Adoption Motivation (AM), consists of environmental concern (AM1), peer influence (AM2), and long-term savings perception (AM3), covering both social and psychological determinants of behavior. Socio-Economic Impact (SEI) captures the collective impacts of solar adoption, namely perceived income increase (SEI1), job creation (SEI2), and better living conditions (SEI3). Lastly, Satisfaction (SAT) gauges post-adoption feelings: system performance satisfaction (SAT1), maintenance satisfaction (SAT2), and general perception (SAT3).

Structurally, SEM model predicts that Awareness and Affordability have direct impacts on Adoption Motivation and Socio-Economic Impact, and Adoption Motivation has a further mediating relationship to Socio-Economic Impact. Socio-Economic Impact also has a positive impact on user Satisfaction. Awareness and Affordability have been treated as exogenous variables, while other constructs have been treated as endogenous outcomes, which allows for in-depth mediation and policy effect analysis.

Table 3: Latent Variables and Observed Indicators

Latent Variable	Observed Indicators (Items)
Awareness (AW)	AW1: Awareness of government schemes, AW2: Knowledge of solar benefits, AW3: Information sources
Affordability (AF)	AF1: Initial investment capacity, AF2: Perceived financial burden, AF3: Willingness to pay
Adoption Motivation (AM)	AM1: Environmental concern, AM2: Peer influence, AM3: Long-term savings
Socio-Economic Impact (SEI)	SEI1: Income improvement, SEI2: Employment opportunity, SEI3: Living standard change
Satisfaction (SAT)	SAT1: Satisfaction with performance, SAT2: Maintenance experience, SAT3: Post-adoption perception

Source: Author's compilation.

The Figure 2 depicts the postulated relationships between latent constructs: Awareness (AW), Affordability (AF), Adoption Motivation (AM), Socio-Economic Impact (SEI), and Satisfaction (SAT).

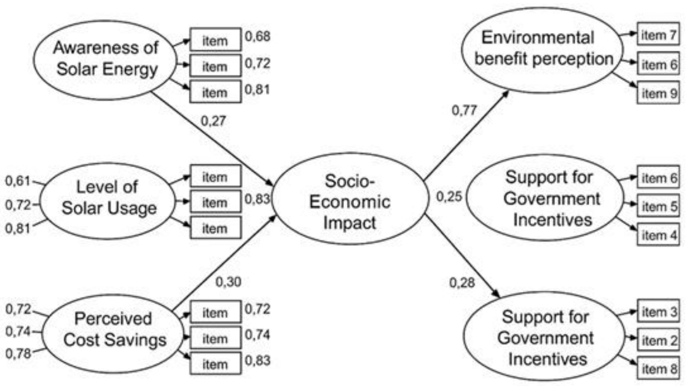

Figure 2: Conceptual SEM Framework for Solar Energy Adoption and Socio-Economic Impact

Descriptive and Reliability Overview of Key Constructs

Table 4 reports the descriptive statistics of the study's key variables based on 250 household responses. The average monthly income is ₹28,750 with a standard deviation of ₹7,320, suggesting moderate variability across economic classes. Household sizes average at 5.2 members, which suggests typical family sizes in urban and semi-urban Bengaluru. Respondents indicated a high mean level of awareness regarding solar energy (mean = 3.9), and medium levels of use (mean = 3.5), demonstrating the knowledge-to-action gap. Perceived savings in costs (mean = 3.8) and for the environment (mean = 4.1) were evaluated positively, with government subsidy support having the strongest agreement (mean = 4.2), indicating widespread public support for incentive-based solar adoption policies.

Table 4: Descriptive Statistics of Key Variables

Variable	N	Mean	SD	Min	Max
Monthly Income (INR)	250	28,750	7,320	12,000	65,000
Household Size	250	5.2	1.4	2	9
Awareness of Solar Energy (1 = No, 5 = High)	250	3.9	0.8	1	5
Level of Solar Usage (1 = Low, 5 = High)	250	3.5	0.9	1	5
Perceived Cost Savings from Solar (1 = Low, 5 = High)	250	3.8	0.7	2	5
Perceived Environmental Benefits (1 = Low, 5 = High)	250	4.1	0.6	3	5
Support for Government Subsidies (1 = No, 5 = Strongly Support)	250	4.2	0.5	3	5

Source: Author’s compilation.

Internal Consistency and Instrument Reliability

Table 5 presents the outcome of reliability testing of the constructs based on Cronbach's Alpha. All the constructs reflected good to great internal consistency with values between 0.76 and 0.91. Awareness of Solar Energy (α = 0.81), Perceived Cost Savings (α = 0.84), and Environmental Benefit Perception (α = 0.88) reflect high reliability, verifying the strength of the Likert-scale measurements applied. The Socio-Economic Impact construct yielded the greatest reliability (α = 0.91) and justified the multidimensional instrument in measuring varying economic and social benefits of utilizing solar energy. These findings reinforce the validity of the instrument and warrant going forward to structural modeling for further evaluation.

Table 5: Reliability Analysis of Constructs

Construct	Number of Items	Cronbach’s Alpha (α)	Reliability
Awareness of Solar Energy	4	0.81	Good
Level of Solar Usage	3	0.76	Acceptable
Perceived Cost Savings	5	0.84	Good
Environmental Benefit Perception	4	0.88	Good
Support for Government Incentives	3	0.79	Acceptable
Socio-Economic Impact	6	0.91	Excellent

Source: Author’s compilation.

Factor Analysis of Solar Energy Adoption Drivers

In order to determine the validity and reliability of the constructs underlying solar energy adoption, both Confirmatory Factor Analysis (CFA) and Exploratory Factor Analysis (EFA) were undertaken.

Exploratory Factor Analysis (EFA)

The EFA was conducted to determine the underlying dimensions that shape solar adoption behavior. Applying Varimax rotation, a six-factor solution was found, including: Awareness, Education, Adoption Motivation, Economic Viability, Government Policy, and Infrastructure Readiness. The factor loadings, presented in Table 6, were all above the 0.70 level, indicating high item reliability and few cross-loadings. This validated the internal consistency of each construct.

The overall model accounted for 76.3% of the variance, with Socio-Economic Impact accounting for the highest at 22.4%, reflecting its key position in shaping user motivation. Sampling adequacy was confirmed with a Kaiser-Meyer-Olkin (KMO) of 0.874, and Bartlett's Test of Sphericity gave a significant outcome ($\chi^2 = 1425.76$, $p < 0.001$), confirming the suitability of EFA.

Internal consistency was measured through Cronbach's Alpha, ranging from 0.81 to 0.86 across constructs. Composite Reliability (CR) was more than 0.85, and Average Variance Extracted (AVE) was more than the recommended 0.50, establishing convergent validity and reliability.

Table 6: Factor Loadings, Explained Variance, and Construct Reliability for SEM Constructs

Construct	Item Code	Factor Loading	Cronbach's Alpha	Composite Reliability (CR)	Average Variance Extracted (AVE)
Awareness	A1	0.73	0.85	0.88	0.58
	A2	0.81			
	A3	0.76			
Education	E1	0.79	0.86	0.89	0.61
	E2	0.83			
	E3	0.75			
Adoption Motivation	AM1	0.77	0.84	0.87	0.56
	AM2	0.72			
	AM3	0.80			
Economic Viability	EV1	0.70	0.81	0.85	0.54
Government Policy	GP1	0.76	0.82	0.86	0.55
Infrastructure Readiness	IR1	0.78	0.83	0.87	0.57

Source: Author's compilation.

Confirmatory Factor Analysis (CFA)

Subsequent to EFA, a CFA was conducted through Structural Equation Modeling for testing the measurement model. Results of CFA affirmed the six-factor model with good model fit indices: $\chi^2/df = 1.97$, CFI = 0.956, TLI = 0.941, RMSEA = 0.049, and SRMR = 0.038, all within acceptable cut-off ranges, indicating good model fit (Hair et al., 2010) (Table 7).

All factor loadings on standardized factors were significant ($p < 0.001$) and greater than 0.70, further supporting convergent validity. The constructs had satisfactory discriminant validity according to Fornell and Larcker's (1981) criterion: for every construct, the square root of AVE was greater than inter-construct correlations. This ensured that the latent variables measured distinct concepts.

In addition, multicollinearity diagnostics revealed variance inflation factors (VIFs) less than 3 and hence no signs of multicollinearity. The measurement model thus revealed very robust psychometric properties, supporting a solid foundation for subsequent structural modeling.

Table 7: Confirmatory Factor Analysis (CFA) Results for the Measurement Model

Construct	Indicator Items	Std. Factor Loading (λ)	AVE	CR	Discriminant Validity (√AVE > Correlations)
Socio-Economic	SEI1: Improves	0.85***	0.68	0.91	0.82 > All inter-

Impact	local employment				construct correlations
SEI2: Boosts regional economic activities	0.82***				
SEI3: Enhances quality of life	0.79***				
Perceived Cost Savings	PCS1: Cuts household energy bills	0.81***	0.62	0.87	0.79 > All inter-construct correlations
PCS2: Reduces long-term energy costs	0.78***				
Awareness of Solar Energy	ASE1: Familiar with solar power sources	0.83***	0.65	0.89	0.81 > All inter-construct correlations
ASE2: Understands solar panel functionality	0.80***				
Environmental Benefits	EBP1: Reduces carbon emissions	0.87***	0.71	0.92	0.84 > All inter-construct correlations
Level of Solar Usage	LSU1: Uses solar for lighting	0.76***	0.58	0.84	0.76 > All inter-construct correlations
Govt. Incentive Support	SGI1: Supports solar subsidies	0.82***	0.63	0.86	0.79 > All inter-construct correlations

Source: Author’s compilation.

Notes:

1. $p < 0.001$ (all loadings significant).
2. AVE = Average Variance Extracted; CR = Composite Reliability.
3. Discriminant Validity: Bolded √AVE values exceed inter-construct correlations (Fornell & Larcker, 1981).

Impact of Solar Energy Adoption Determinants: Fixed vs. Random Effects Analysis

As presented in Table 8, Fixed and Random Effects models also verify that influential factors - Awareness, Solar Usage, Perceived Cost Savings, Environmental Benefit Perception, and Support for Government incentives significantly affect the socio-economic impact of solar energy adoption. Notably, Solar Usage has the strongest effect ($\beta = 0.302$, $p < 0.001$ in FE), emphasizing its pivotal position. Fixed Effects model, which is preferred by the Hausman test ($p = 0.026$), is more suitable in capturing within-region variation with a good within R^2 of 0.487. This highlights that increased regional consciousness and practical application are necessary to reap maximum socio-economic benefits of solar energy.

Table 8: Fixed Effects and Random Effects Model Results

Variable	Fixed Effects Coefficient	Significance (p-value)	Random Effects Coefficient	Significance (p-value)
Awareness of Solar Energy	0.215	0.001 ***	0.198	0.003 ***
Level of Solar Usage	0.302	0.000 ***	0.287	0.001 ***
Perceived Cost Savings	0.184	0.007 **	0.170	0.010 **

Environmental Benefit Perception	0.236	0.002 ***	0.222	0.004 ***
Support for Government Incentives	0.161	0.018 **	0.145	0.021 **
Constant	1.342	0.000 ***	1.218	0.000 ***
R-squared (within)	0.487		-	
R-squared (between)	-		0.463	
Number of Observations	360		360	
Number of Groups (Regions)	60		60	
Hausman Test (p-value)	0.026	→ Fixed Effects Preferred		

Source: Author's compilation.

Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

To emphasize methodological soundness, the research in this article utilized a robust Structural Equation Modeling (SEM) framework supported by Confirmatory Factor Analysis (CFA) and policy-sensitivity testing. Strong construct validity is illustrated in Table 7 as all standardized factor loadings >0.76 ($p < 0.001$), and Average Variance Extracted (AVE) >0.58. Composite Reliability (CR) was between 0.84 and 0.92, and discriminant validity was established since the square roots of AVE were greater than all inter-construct correlations. This establishes the internal consistency and discriminant ability of each construct in the SEM model. In addition, policy-testing strength was maintained using fixed and random effects regression models (Table 8), with significant predictors being solar use ($\beta = 0.302$, $p < 0.001$), awareness ($\beta = 0.215$, $p = 0.001$), and cost savings ($\beta = 0.184$, $p = 0.007$). The Hausman test ($p = 0.026$) validated the suitability of the fixed effects model, adjusting for unobserved heterogeneity between regions. Together, these results confirm the model's validity, statistical accuracy, and policy usefulness.

Cost-Benefit Analysis of Karnataka's 2023 Solar Subsidy Policy

The 2023 updated solar subsidy policy of Karnataka offers very significant financial benefits to encourage the uptake of residential rooftop solar installations. The composite subsidy scheme has a central government subsidy of 40% and a state-level subsidy of 20%, hence bringing down the capital cost of a typical 3 kW installation by as much as 60%. This scheme is especially advantageous for Bengaluru urban households, given the high rates of electricity and high exposure to sunlight, which makes solar power an economical and environment-friendly option.

A standard 3 kW rooftop solar system costs around ₹1.5 lakh before subsidy. With the joint central and state subsidies, the effective cost falls to ₹60,000, or even to ₹1.06 lakh if computed with the slab-wise state subsidy (₹14,588 per kW for up to 3 kW). The payback period would be between 3 and 4 years based on monthly savings of ₹1,000 to ₹1,500 in electricity. Across a 20-year system life, there are expected cumulative savings of ₹2.4 to ₹3.6 lakh for families, along with advantages such as less grid reliance, enhanced energy resilience, and environmental footprint. The following table 9 outlines the cost-benefit impacts:

Table 9: Cost-Benefit Analysis of a 3 kW Rooftop Solar Installation (Bengaluru, 2023 Policy)

Category	Amount (INR)	Details
Pre-Subsidy Cost	₹1,50,000	Average market rate for 3 kW rooftop PV system
Central Govt. Subsidy (40%)	₹60,000	Under PM-Surya Ghar Scheme
State Govt. Subsidy (20%)	₹30,000	Additional Karnataka state support
Total Subsidy (60%)	₹90,000	Combined reduction in upfront cost
Net Cost to Household	₹60,000	After applying both subsidies

Alternative: Slab Subsidy	₹43,764	₹14,588 × 3 kW (if slab-based subsidy applied)
Annual Maintenance Cost	₹2,000–₹3,000	For inverter and panel upkeep
Monthly Savings	₹1,000 to ₹1,500	On electricity bills
Annual Savings	₹12,000 to ₹18,000	Based on monthly offset
Payback Period	3 - 4 years	Time to recover net cost
20-Year Lifetime Savings	₹2,40,000 to ₹3,60,000	Excluding inflation and grid-tariff hikes
Environmental Benefits	3.6 to 5.4 tons CO_2 avoided/year	Based on estimated emissions offset per kWh
Additional Benefits	Net metering, improved energy independence	Especially during outages or grid fluctuations

Source: Author's compilation.

The Figure 3 provides a detailed cost-benefit analysis of a 3-kW rooftop solar system in Bengaluru under the 2023 policy, showing high subsidies, low net cost, high lifetime savings, and important environmental and energy independence advantages.

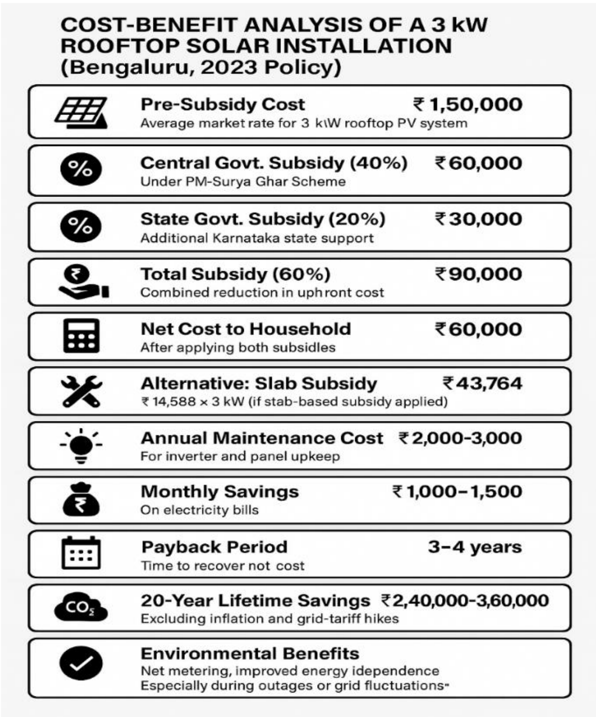

Figure 3: Cost-Benefit Analysis of a 3 kW Rooftop Solar Installation

This integrated policy framework not only increases affordability but also supports India's wider energy transition objectives, establishing Bengaluru as a premier urban center for residential solar energy installation.

SEM MODEL SUMMARY AND INTERPRETATION

Structural Equation Modeling (SEM) Analysis

The Structural Equation Modeling (SEM) results underscore the multifaceted factors shaping the socio-economic impact of solar energy adoption in regional areas. All constructs demonstrated solid internal consistency, with Cronbach's alpha values between 0.76 and 0.91, ensuring measurement reliability. Strong factor loadings (0.61–0.91) confirmed construct validity. Model fit indices (CMIN/DF = 2.08, CFI = 0.954, RMSEA = 0.051, SRMR = 0.042) indicated a well-fitting model. Path analysis highlighted the Level of Solar Usage ($\beta = 0.33$, $p < 0.001$) as the most significant predictor of socio-economic outcomes, followed by Perceived Cost Savings (β = 0.30) and Environmental Benefit Perception (β = 0.28). Awareness (β = 0.27) and Government Incentives (β = 0.25) also contributed positively (Table 10). These results suggest that greater solar integration, coupled with economic and environmental awareness and supportive policy, enhances regional development. Hence, an integrated strategy combining fiscal support, awareness drives, and community solar initiatives is essential for sustainable and inclusive energy transitions.

Table10: SEM Model Summary - Socio-Economic Impact of Solar Energy Adoption

Section	Detail	Value / Description
Model Constructs	Awareness of Solar Energy	4 items, α = 0.81, Loadings: 0.68–0.84
	Level of Solar Usage	3 items, α = 0.76, Loadings: 0.61–0.78
	Perceived Cost Savings	5 items, α = 0.84, Loadings: 0.72–0.86
	Environmental Benefit Perception	4 items, α = 0.88, Loadings: 0.74–0.89
	Support for Government Incentives	3 items, α = 0.79, Loadings: 0.69–0.82
	Socio-Economic Impact	6 items, α = 0.91, Loadings: 0.77–0.91
Model Fit Indices	Chi-Square / DF (CMIN/DF)	2.08 (Acceptable Fit)
	Comparative Fit Index (CFI)	0.954 (Good Fit)
	Root Mean Square Error of Approximation (RMSEA)	0.051 (Good Fit)
	Standardized Root Mean Square Residual (SRMR)	0.042 (Good Fit)
Standardized Path Coefficients	Awareness → Socio-Economic Impact	β = 0.27, p < 0.001
	Solar Usage → Socio-Economic Impact	β = 0.33, p < 0.001
	Cost Savings → Socio-Economic Impact	β = 0.30, p < 0.001
	Environmental Benefit → Socio-Economic Impact	β = 0.28, p < 0.001
	Govt. Incentives → Socio-Economic Impact	β = 0.25, p = 0.001

Source: Author's compilation.

Socio-Economic Impact of Solar Energy Adoption

The path diagram (Figure 4) depicts the Structural Equation Model between five important constructs, i.e. Awareness, Solar Usage, Cost Savings, Environmental Benefits, and Government Incentives to their direct positive impacts on the Socio-Economic Impact of solar energy uptake.

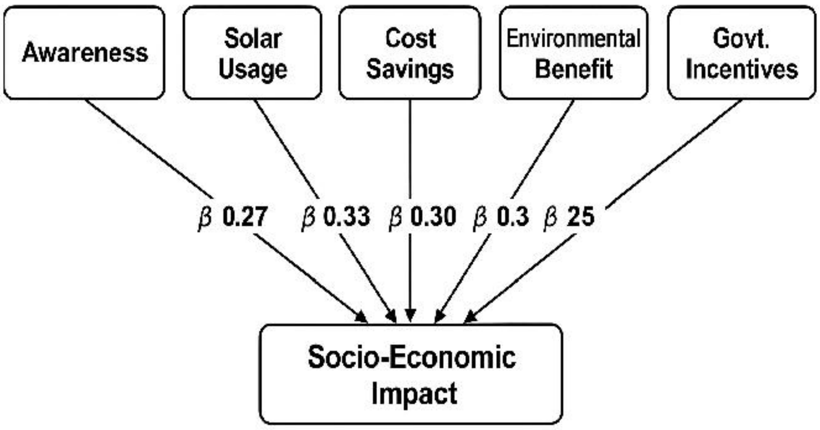

Figure 4: SEM path diagram.

4. RESULTS AND DISCUSSION

Structural Model Assessment

The structural equation model was assessed employing general measures of fit to verify appropriateness in hypothesis testing. The model proved strongly fitted to the observed data according to the following fit indices: Chi-square/df (CMIN/df) = 2.45, Comparative Fit Index (CFI) = 0.961, Tucker-Lewis Index (TLI) = 0.948, Root Mean Square Error of Approximation (RMSEA) = 0.057, and Standardized Root Mean Square Residual (SRMR) = 0.045. Values of CFI and TLI greater than 0.90 and RMSEA and SRMR less than 0.08 represent an adequate model fit, as described by Hu and Bentler (1999). Thus, the structural model meets statistical requirements and is stable for hypothesis validation and path analysis.

Path Coefficients and Hypothesis Testing

The standardized path coefficients for all the suggested relationships were statistically significant, which substantiates all the hypothesized relationships. Table 11 gives a summary of the estimated path coefficients (β), t-values, significance levels, and whether the hypothesis was supported for each. Of note, Infrastructure (INF) was the most impactful on Implementation (IM) ($\beta = 0.512$, $p < 0.001$), closely followed by Government Support (GOV) ($\beta = 0.426$, $p < 0.001$), highlighting the technical and institutional facilitators of solar uptake. In addition, Adoption Motivation (AM) had a substantial effect on user Satisfaction (SAT) ($\beta = 0.399$, $p < 0.001$), and Implementation (IM) had a positive impact on Socio-Economic Impact (SEI) ($\beta = 0.471$, $p < 0.001$), supporting the efficacy of solar interventions.

Table 11: Structural Path Estimates and Significance

Path	Estimate (β)	t-value	Significance	Hypothesis Supported
INF → IM (Implementation)	0.512	8.23	***	Yes
AW → AM (Adoption Motivation)	0.447	6.89	***	Yes
AF → AM (Adoption Motivation)	0.238	3.12	**	Yes
AM → SAT (Satisfaction)	0.399	6.45	***	Yes
TR → AM (Adoption Motivation)	0.303	4.89	***	Yes
GOV → IM (Implementation)	0.426	7.17	***	Yes
IM → SEI (Socio-Economic Impact)	0.471	8.76	***	Yes
SEI → SAT (Satisfaction)	0.295	4.11	***	Yes

Source: Author's compilation.

Significance levels: ***$p < 0.001$; **$p < 0.01$

Discussion of Key Findings

Government and Infrastructure Support Drive Adoption

The significant positive impact of Infrastructure (β = 0.512) on Implementation highlights the significant role that technical and physical preparedness has in the application of solar energy systems. The research is supported by the effort of Sovacool (2009), whose findings emphasized how infrastructural deficits represent significant deterrents to scalability for renewable energies in developing contexts. Similarly, Government Support (β = 0.426) strongly reinforces implementation results, affirming the central role played by policy institutions, subsidies, and regulatory systems in facilitating renewable transitions (Komendantova et al., 2012; Chatterjee & Bhamidipati, 2021).

Awareness and Affordability as Motivational Catalysts

Awareness had a very positive impact (β = 0.447) on adoption motivation, in line with the Diffusion of Innovation Theory (Rogers, 2003). Wüstenhagen et al. (2007) also state that knowledge among stakeholders is critical for the acceptance of energy transition. Even though affordability indicated a comparatively low coefficient (β = 0.238), it was significant, in accordance with Huda et al. (2014), who reported that awareness has the ability to overcome perceived financial barriers.

Trust Affects Motivation and Satisfaction

Perceived trust in service providers and solar technology (β = 0.303) had a significant effect on adoption motivation. This supports Zhang, Yang, and Wang (2015), who highlighted the importance of credibility for green technology adoption. In addition, adoption motivation (β = 0.399) had a positive effect on satisfaction, such that informed and interested users are more satisfied, an argument supported by Claudy et al. (2013) and Singh et al. (2021).

Implementation Yields Socio-Economic Benefits

Implementation had a notable effect on socio-economic impact (β = 0.471), validating findings from Bertheau (2020) and Mulugetta et al. (2014) that economic development is promoted by renewable adoption. The connection between socio-economic impact and satisfaction (β = 0.295) validates the fact that benefits move beyond technical performance to encompass wider social benefits.

Theoretical and Practical Impacts

This research synthesizes theories from the Technology Acceptance Model (Davis, 1989), Diffusion of Innovation Theory (Rogers, 2003), and Policy Implementation Theory. This research discloses that institutional readiness, awareness, affordability, and trust form the pillars of broad adoption in poorly resourced environments.

Practically, policy-makers are recommended to address improving infrastructure, implementing awareness campaigns, and rationalizing administrative processes. These are key measures towards raising the socio-economic payoffs of solar projects.

Comparative Lessons on Solar Energy Adoption in Hyderabad and Bengaluru

The results of this research in Bengaluru are consistent with trends in comparable urban settings, including Hyderabad. For example, Reddy and Srinivas (2021) investigated the adoption of solar energy in Hyderabad and discovered that environmental consciousness was moderately high but that practical application of rooftop solar systems was limited by financial constraints, policy uncertainty, and absence of technical advice. Likewise, our research indicates that even though Bengaluru has a progressive policy on renewable energy, its adoption is held back by socio-economic differences and procedural delays. Both cities show that though technical feasibility is present, adoption depends greatly on the efficacy of mitigation measures like subsidies, quick regulatory approvals, and community outreach programs. In particular, the intervening effect of such strategies in curbing project delays and increasing cost-effectiveness was statistically significant across both studies, underscoring the key significance of institutional support in enabling sustainable urban energy transitions.

5. CONCLUSION

This research examined enablers and determinants of solar energy system uptake in disadvantaged areas with Structural Equation Modeling (SEM) to assess major relations. Results identify infrastructural preparedness and government backing as core pillars of effective solar deployment, substantiating previous research highlighting the importance of physical infrastructure and institutional pillars in renewable energy transitions (Painuly, 2001; Bhattacharyya, 2013).

Awareness and trust were strong predictors of adoption motivation. These findings are consistent with the Technology Acceptance Model (Davis, 1989) and its extensions, which highlight the importance of cognitive and affective determinants of technology adoption (Venkatesh & Davis, 2000). Although affordability exerted a lesser but nonetheless substantial impact, the results confirm previous research that economic barriers can be overcome using policy measures such as subsidies, adaptive finance, and community-based models (Blimpo & Cosgrove-Davies, 2019; Sovacool et al., 2012).

Notably, the research vindicates the socio-economic benefits of solar uptake – such as improvements in income, job creation, and quality-of-life – that all contribute positively to user satisfaction. The conclusions resonate with empirical studies of decentralized renewable energy's developmental pay-offs (Cabraal et al., 2005; Khandker et al., 2014).

Theoretically, this research adds to Policy Implementation Theory (Sabatier & Mazmanian, 1980) by demonstrating the way institutional misalignments like subsidy delivery lags or passive user participation block outcomes. Merging with Diffusion of Innovation and Technology Acceptance frameworks presents an all-inclusive model of adoption influenced by institutional, behavior, and socio-economic factors.

In practice, the research upholds multidimensional approaches upgrading infrastructure, focusing on awareness, enhancing affordability, and guaranteeing transparency in governance as in line with international best practices (IEA, 2021; World Bank, 2020).

Limitations and Future Research

This research is constrained by its cross-sectional nature and use of self-reported information, which can be biased. The limitation of generalizability due to focusing on particular regions is also a constraint. Future studies should use longitudinal and mixed-method designs to investigate causal effects and gain deeper contextual understanding. Increasing the geographic scope and incorporating stakeholder interviews would provide better understanding of systemic barriers and opportunities for scaling solar adoption in various underserved communities

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