

FINANCIAL INCENTIVES DRIVE QUEENSLAND HOME-SOLAR UPTAKE: EVIDENCE FROM SEM

PATRICK CHERUIYOT, MATTHEW MOORHEAD and JASPER MBACHU

Bond University, Gold Coast, Australia

ABSTRACT

This study examines causal pathways underpinning residential solar photovoltaic (SPV) adoption in Queensland, Australia. Using survey data (n = 574) and partial least squares structural equation modelling (PLS-SEM), we test direct effects and mediations among Financial, Policy-Regulations, Socio-Environmental and Technological constructs. The measurement model shows strong, significant loadings. In the structural model, the Financial → Uptake path is large and significant, whereas direct paths from Policy-Regulations, Socio-Environmental and Technological constructs to uptake are weak or non-significant. Mediation tests show that policy works primarily through finance: Policy-Regs → Financial → Uptake and Technological → Financial → Uptake are significant. Total effects confirm strong policy links via financial and technological channels despite a non-significant direct policy effect. Findings indicate financial mechanisms (bill savings, expectations of future costs, property rights/homeownership) remain pivotal levers in a mature SPV market. Policy stability and targeted financial instruments are likely to outperform stand-alone technological or environmental messaging

Keywords: Residential Solar PV, Structural Equation Modelling, Causal Relationships, Policy Regulations, Financial Factors, Australia

INTRODUCTION

Australia leads the world in residential solar photovoltaic (PV) adoption, with over 3 million households installing systems by 2022 (Clean Energy Regulator, 2022). This shift has been driven by falling solar technology costs, rising electricity bills, and heightened awareness of environmental issues. Within Australia, Queensland stands out with the highest rate of residential solar PV uptake, earning it the reputation of a national leader in distributed solar generation. Despite this success, adoption is not universal. Evidence suggests that low-income households, renters, and residents of multi-unit dwellings face unique barriers to participation in the solar transition. These challenges point to a growing equity gap in Australia's clean energy shift—raising important questions about who benefits from solar subsidies, and under what conditions adoption occurs.

The decision to adopt solar PV is shaped by a complex mix of financial, policy, socio-environmental, and technological factors. While earlier studies have identified individual drivers (e.g., income, environmental concern, or rebate access), few have modelled how these factors interact or influence adoption through causal pathways. Moreover, the role of policy, particularly in mature markets like Queensland, may no longer act directly, but instead operate through financial and social intermediaries. Understanding these relationships is essential for designing more effective and inclusive policy interventions.

This study addresses these gaps using Structural Equation Modelling (SEM) and machine learning (ML) analysis. Survey data from 574 Queensland households is analysed to investigate the direct, mediated, and moderated relationships among key adoption factors. SEM is used to test the causal links between financial, policy, socio-environmental, and technological constructs, while Random Forest modelling highlights the most influential demographic and contextual variables.

The findings reveal that financial considerations, including electricity bills, installation cost, and perceived savings, remain the most significant direct drivers of solar adoption. Policy factors such as feed-in tariffs and rebates exert an indirect effect, mediated through their influence on financial feasibility. Additionally, variables such as homeownership, grid connectivity, and access to information emerge as significant in shaping household-level decisions. Through the integration of SEM with machine learning feature analysis, this study contributes a novel methodological approach to the solar adoption literature. It also offers practical insights for policymakers aiming to close adoption gaps and design more targeted solar incentive programs.

LITERATURE REVIEW

Understanding the drivers of residential solar PV adoption requires a multi-dimensional approach, recognising the interplay between financial, policy, socio-environmental and technological factors. While individual factors have been well documented, limited work has explored their combined effects through structural modelling. This section reviews the existing literature to establish the foundation for the study's conceptual model.

Financial Drivers

Financial factors are consistently identified as the most influential determinant in residential solar PV adoption. High upfront costs for system purchase and installation continue to pose a major barrier for many households (Zander et al., 2019). However, financial incentives, such as government rebates, feed-in tariffs, and low-interest financing options, help offset these costs, increasing system affordability and uptake (Best et al., 2021; Rai et al., 2016). Studies show that anticipated savings on electricity bills and long-term return on investment are powerful motivators (Islam & Meade, 2013).

Access to financing also plays a critical role. Briguglio and Formosa (2017) found that households with access to loans or leasing arrangements were significantly more likely to install solar systems. Perceived economic benefit, financial literacy, and an understanding of payback periods can influence decision-making (Rai et al., 2016). Income, however, is a debated factor. While some studies suggest that high-income households dominate adoption (Mills & Schleich, 2014), others have found uptake to be growing across income brackets when incentives are well targeted (Sommerfeld et al., 2017).

Policy and Regulatory Context

Policy mechanisms shape adoption both directly and indirectly. Government schemes such as the Small-Scale Renewable Energy Scheme (SRES), state-based rebates, and feed-in tariffs have driven Australia's solar boom since the early 2000s (Clean Energy Regulator, 2022). Best et al. (2021) argued that while initial uptake was strongly policy-driven, recent adoption patterns are more dependent on financial perceptions than on policy visibility alone. Regulatory simplicity is also critical. Complex application processes, varying eligibility criteria, and inconsistent rebate levels between states can confuse or discourage potential adopters (Dharshing, 2017). Studies have shown that where regulations are streamlined and accessible, adoption tends to rise (Islam & Meade, 2013). Policy effects may also be mediated through financial constructs. That is, households may not adopt solar because of a rebate, but because the rebate changes their financial perception of the feasibility of solar installation. This distinction is central to this study's structural model.

Socio-Environmental Factors

Socio-environmental factors encompass a broad range of motivations and contextual influences that extend beyond financial calculations. These include environmental concern, climate change awareness, peer influence, social norms and perceived behavioural control, all of which can influence the intention to adopt renewable technologies like solar PV (Jager, 2006; Ajzen, 1991). Environmental concern has long been associated with pro-environmental behaviour, including the uptake of solar energy (Zander et al., 2019; Zander, 2021; Wolske et al., 2020). In Australia, public support for clean energy is high, yet this support does not always translate into action. This phenomenon, commonly referred to as the intention-behaviour gap, is often due to the absence of enabling conditions, such as affordability, supportive policy or social reinforcement (Bamberg & Möser, 2007).

Social influence is a particularly important factor in Australia's context. Bollinger and Gillingham (2012) found that peer effects can account for up to 20% of residential solar PV installations in certain US neighbourhoods. This pattern is likely similar in Australia, where solar panels are highly visible on rooftops, potentially reinforcing adoption through visual cues and word-of-mouth recommendations. Social norms, community-level adoption rates, and even local council campaigns have all been found to influence household decision-making (Rai & Robinson, 2015).

Additionally, perceived behavioural control, or the sense that one has the ability, knowledge and authority to adopt solar, may also impact adoption, particularly among renters or those in shared housing arrangements. In

Queensland, where rates of homeownership are relatively high, the potential for control-based constraints may be less than in more transient rental markets. Still, for certain demographics such as young adults, non-English speaking households or low-income renters, a lack of decision-making autonomy or confidence may deter uptake (Sommerfeld et al., 2017). Although socio-environmental motivations may not always act directly, they often exert indirect effects, reinforcing financial justifications or increasing acceptance of government programs. These relationships justify their inclusion in the SEM model as potential latent constructs influencing other more tangible drivers.

Technological Considerations

Technological perceptions are often underestimated in solar adoption research but can be critical in influencing household decisions, particularly for non-expert users. These perceptions include concerns about system reliability, performance variability, installation complexity and maintenance requirements (Balcombe et al., 2014). In the Australian market, where solar systems are relatively mature and reliable, these concerns have lessened but remain present in certain demographic groups. One common barrier is lack of information about system performance, panel efficiency, battery storage options and grid interaction. This aligns with research by Claudy et al. (2011), who found that perceived complexity and uncertainty can reduce willingness to adopt green technologies. For homeowners unfamiliar with technical jargon, even minor doubts about technology lifespan or inverter function can delay or prevent adoption.

An increasingly relevant technological factor is the integration of solar systems with the smart grid. Households are no longer just energy consumers but are becoming “prosumers”, producing and consuming energy, often with battery storage and real-time energy management tools (Claudy et al., 2013). However, awareness of this capability and trust in the supporting technology are still developing. Studies suggest that adopters with a higher degree of technological self-efficacy are more likely to consider solar–battery integration (Wolske et al., 2020).

Trust in installers and brands also shapes technological perceptions. Inconsistent quality among suppliers, coupled with a history of misleading sales practices in the early 2010s, has contributed to residual scepticism in the market (Simpson, G., 2018). Assurance via certification schemes, government-endorsed providers, or word-of-mouth recommendation can mitigate these concerns. Importantly, technological considerations rarely operate in isolation. They often intersect with financial and policy variables. For example, uncertainty about battery efficiency may dissuade investment unless rebates are generous. Similarly, grid export limitations or technical restrictions can undermine perceptions of value, particularly for high-producing households.

In the present study, technological factors are modelled as a latent construct within the SEM framework, capturing household perceptions of system reliability, ease of installation, performance satisfaction and grid compatibility. Although these may not be the primary drivers, their interaction with financial and policy perceptions may significantly influence adoption decisions.

Gaps in the Literature and Research Contribution

There exists a gap in many prior studies of a structural understanding of how these drivers interact. For instance, policy incentives may only be effective if financial literacy is high. Similarly, environmental concern may translate into adoption only if supported by peer behaviour and social norms. While several European studies have explored the mediating role of financial drivers in renewable energy adoption (e.g., through economic modelling or market valuation), there is a gap in the literature applying SEM to disentangle these relationships in national contexts like Australia. Similar findings have emerged in North America (Wolske et al., 2017) and Asia (Lau et al., 2020), though such models are rarely tested in the Australian context. A further limitation of prior SEM studies is the omission of technological perceptions and regulatory complexity as latent variables. This study addresses this gap by developing and testing a conceptual model in which financial perceptions mediate the effects of policy, social, and technological drivers. Moreover, machine learning (Random Forest) is employed to validate the relative importance of key features, allowing the identification of strong non-linear predictors outside the causal path.

Despite Australia’s leadership in residential solar adoption, there is limited structural modelling of uptake decisions in mature policy environments like Queensland. Many prior studies are either descriptive or rely on linear regression, missing the dynamic interplay between household-level perceptions and broader institutional

signals. Moreover, existing models do not sufficiently explore mediating effects of financial perceptions or moderating effects of demographic variables like homeownership, urban location, and household size.

This study contributes to the literature in three key ways:

- It applies SEM to test a multi-factor model of solar PV adoption using data from 574 Queensland households.
- It integrates machine learning to identify non-linear, contextual predictors of adoption, including homeownership and grid connectivity.
- It highlights the mediating role of financial feasibility, showing how policy and social factors influence adoption through economic perceptions.

By combining causal modelling with feature ranking, the study offers both theoretical insight and practical recommendations for solar adoption policy in developed, deregulated energy markets.

METHODOLOGY

This study employs a mixed-method quantitative design combining SEM with Random Forest (RF) classification to examine the drivers of residential solar PV adoption among households in Queensland, Australia. SEM is used to assess causal pathways and latent variables, while RF provides a complementary feature importance analysis that captures non-linear relationships often missed in traditional modelling.

Research design

The research uses a cross-sectional survey design to gather data on household demographics, financial perceptions, policy awareness, social influences and technological attitudes. The approach is grounded in established theoretical frameworks such as the Theory of Planned Behaviour (Ajzen, 1991) and innovation adoption literature (Rogers et al., 2014) but extends this work through SEM's ability to test mediating and moderating effects simultaneously. This dual-modelling strategy allows for both theory-driven hypothesis testing and data-driven variable importance estimation.

Survey Instrument

The survey was designed using validated scales adapted from prior literature. It comprised five key latent constructs, each measured using Likert-scale items (1 = Strongly Disagree to 5 = Strongly Agree):

- Financial Feasibility: Items adapted from Islam & Meade (2013), focusing on cost perception, payback period, and affordability.
- Policy Awareness: Items based on Clean Energy Regulator (2022) data, assessing familiarity with rebates, tariffs, and grid export rules.
- Social Influence: Peer adoption, social norms, and environmental values (adapted from Wolske et al., 2017; Jager, 2006).
- Technological Confidence: Reliability, complexity, and compatibility perceptions (informed by Balcombe et al., 2014).
- Adoption Intention / Behaviour: Self-reported adoption or stated likelihood to adopt solar within 12 months.

The final instrument contained 32 items, including socio-demographics (age, income, household size, tenure) and postcode for regional analysis.

Data collection

Data were collected via a Qualtrics online survey administered in late 2023 using a professional panel provider, targeting residents across Queensland. Stratified sampling ensured representation across urban, suburban, and regional households. A total of 574 valid responses were received. The sample was representative by age, homeownership status, and solar adoption rates based on AEMO (2023) and Clean Energy Regulator (2022) data.

To ensure quality, the survey included:

- Screening questions for residency and homeownership

- Time-threshold filters (minimum 3 minutes)
- Reverse-coded items for reliability

Data preparation and cleaning

Data preparation involved the following steps:

- Removal of incomplete responses ($n = 18$)
- Recoding of negatively worded items
- Z-score standardisation for RF input
- Latent variable construction using average item scores

Normality was assessed using skewness and kurtosis statistics. While some variables were slightly non-normal, SEM estimation proceeded using maximum likelihood with robust standard errors (MLR), appropriate for non-normal data (Hair et al., 2019; Hair & Alamer, 2022).

Missing data were minimal (<2%) and addressed using expectation-maximisation (EM) imputation.

Structural equation modelling (SEM)

SEM was performed using AMOS 29. The model tested the following hypotheses:

- H1: Policy Awareness → Financial Feasibility (+)
- H2: Social Influence → Financial Feasibility (+)
- H3: Technological Confidence → Financial Feasibility (+)
- H4: Financial Feasibility → Solar Adoption (+)
- H5: Financial Feasibility mediates all indirect effects on Adoption

The model included four exogenous latent variables and one endogenous latent outcome (adoption intention). A path diagram was constructed based on theory and empirical grounding.

Model fit was assessed using multiple indices:

- Chi-square (χ^2) = 274.3, $df = 138$, $p < 0.001$
- CFI = 0.964 (≥ 0.95 acceptable)
- RMSEA = 0.048 (≤ 0.06 good fit)
- SRMR = 0.039 (≤ 0.08 acceptable)

All latent constructs demonstrated high reliability (Cronbach's $\alpha > 0.80$). Convergent validity was supported by AVE > 0.50 for all constructs. Discriminant validity was confirmed via Fornell-Larcker criteria. Mediation was tested using bootstrapping (5000 samples) and showed that financial feasibility fully mediated the effects of policy, social, and technological variables on adoption ($p < 0.05$).

Random Forest (RF) Analysis

To complement SEM, a Random Forest classification model was developed using Scikit-learn in Python. The dependent variable was solar adoption status (binary: adopter vs. non-adopter). Input variables included both latent and observed features (e.g., income, homeownership, FiT knowledge).

Model parameters:

- Trees: 100
- Max depth: unlimited
- Criterion: Gini

Model accuracy was 91.3% on test data (20% holdout), with strong precision (0.87) and recall (0.92). The top predictors ranked by feature importance were:

- Financial Feasibility
- Homeownership
- Technological Confidence

- Policy Awareness
- Household Income

The RF model validated the SEM findings, particularly the importance of financial perception and homeownership as dominant predictors. It also highlighted non-linear interactions missed by linear models.

RESULTS

This section presents the findings from the quantitative analysis of solar PV adoption based on data collected from 574 Queensland households. The results are presented in four parts: (1) measurement model assessment; (2) structural model outcomes and hypothesis testing; (3) mediation analysis; and (4) supplementary analyses including Random Forest and historical policy data.

Measurement model

The measurement model was evaluated using Confirmatory Factor Analysis (CFA) in AMOS. Construct reliability and validity metrics indicated acceptable psychometric properties across all latent variables:

- Composite Reliability (CR): All constructs exceeded the 0.70 threshold (range: 0.78 to 0.91).
- Average Variance Extracted (AVE): All constructs showed $AVE > 0.50$, supporting convergent validity.
- Discriminant Validity: Met via Fornell-Larcker criterion; the square root of each construct’s AVE exceeded inter-construct correlations.

Factor loadings ranged from 0.61 to 0.89 and were statistically significant ($p < 0.001$), confirming strong item contributions to their respective latent constructs.

Structural model and hypothesis testing

The structural model assessed the relationships between policy awareness, social influence, technological perceptions, financial feasibility, and solar PV adoption intention. Model fit indices were acceptable:

- $\chi^2 = 274.3$, $df = 138$, $p < 0.001$
- Comparative Fit Index (CFI) = 0.964
- Root Mean Square Error of Approximation (RMSEA) = 0.048
- Standardized Root Mean Residual (SRMR) = 0.039

All hypothesised direct paths were significant as shown in Table 1 below.

Table 1: Hypothesis testing summary: direct effects in the SEM model

Hypothesis	Path	Std. Coeff.	Significance
H1	Policy Awareness → Financial Feasibility	0.41	$p < 0.001$
H2	Social Influence → Financial Feasibility	0.32	$p < 0.01$
H3	Technological Confidence → Financial Feasibility	0.29	$p < 0.01$
H4	Financial Feasibility → Adoption Intention	0.47	$p < 0.001$

Source: Authors

These results suggest that financial feasibility is a key mediating construct, linking upstream drivers (policy, social, and technological) with adoption intention.

Mediation analysis

Bootstrapping with 5,000 samples confirmed full mediation through financial feasibility:

The indirect effects of policy awareness, social influence, and technological confidence on adoption were all significant when mediated via financial feasibility ($p < 0.05$). Direct paths from policy, social, and tech

constructs to adoption were non-significant when mediation was included, supporting a full mediation model. This supports the model's central thesis: households evaluate solar adoption primarily through a financial lens, even when motivated by environmental, social, or policy factors.

Supplementary Analysis: Random Forest Classifier

To contextualise the adoption patterns, two complementary analyses were conducted: (1) historical economic trends and (2) predictive modelling using a Random Forest (RF) classifier.

Historical policy and cost trends

Archival data were analysed to observe annual trends in financial incentives and cost structures relevant to household solar PV adoption. Table 2 presents percentage changes in PV installations, feed-in tariffs (FiT), levelised cost of electricity (LCOE), and rebate values between 2009 and 2013.

Table 2: Annual percentage change in PV adoption and related economic variables (2009–2013)

Year	% Change - PV Installations	% Change - FiT (Tariff)	% Change - LCOE	% Change - Rebates
2009	0%	0%	0%	0%
2010	1271%	0%	2%	-5%
2011	17%	0%	-39%	-5%
2012	-4%	0%	-43%	-5%
2013	-42%	-84%	-18%	-5%

These results illustrate the strong policy sensitivity of solar uptake. The dramatic 1271% surge in installations in 2010 occurred alongside stable FiT and rebate values, while the 84% reduction in FiT by 2013 corresponded to a 42% drop in new installations. This reinforces the influence of financial incentives and cost perception on consumer adoption. This aligns with spatial-temporal modelling insights by Copiello & Grillenzoni (2021), who emphasised the role of policy timing and regional characteristics in solar deployment patterns.

Predictive Modelling with Random Forest

A Random Forest classifier was used to identify the most important features influencing adoption intention and to validate the SEM model findings using a non-linear machine learning approach.

- Model Accuracy: 91.3% (20% test split)
- Top Predictors (Feature Importance):
 - Financial Feasibility (most important)
 - Homeownership Status
 - Technological Confidence
 - Household Income
 - Policy Awareness

These results reinforce the centrality of financial drivers and structural access factors (e.g., homeownership) in shaping adoption. The high classification accuracy suggests that the RF model captured key behavioural patterns. However, as a non-parametric approach, RF does not identify the direction or strength of causal relationships, but complements SEM by identifying feature significance.

Summary

The results provide robust empirical support for the theoretical model. Financial feasibility fully mediates the impact of policy, social, and technological factors on solar adoption. SEM and RF findings align, strengthening the argument that while environmental and policy considerations matter, they are filtered through financial perceptions.

DISCUSSION

This study aimed to understand the determinants of household solar PV adoption in Queensland by integrating policy, social, technological, and financial drivers into a structural equation model (SEM) supported by Random Forest (RF) validation. The discussion reflects on the implications of the findings in light of previous research, with attention to theoretical and policy relevance.

The central role of financial feasibility

The most salient finding is the central mediating role of financial feasibility. While policy awareness, social norms, and technological attitudes were all significantly associated with financial perceptions, only financial feasibility directly predicted adoption intention. This suggests that economic interpretation dominates the decision-making process, echoing conclusions drawn in North American studies (Wolske et al., 2017) and supporting the Theory of Planned Behaviour's emphasis on perceived behavioural control (Ajzen, 1991). Even where environmental concern or peer influence is present, adoption appears to hinge on an individual's cost–benefit assessment.

Limited influence of policy and social norms (direct)

Interestingly, policy awareness and social norms did not have direct effects on adoption once financial feasibility was accounted for. This diverges from an earlier Australian study (Simpson, 2018), which highlighted community advocacy and peer diffusion as direct motivators. This difference may reflect regional variations or a maturation of the Australian PV market. As systems become less novel, social pressure may decline in importance relative to economic rationality, particularly in areas where solar saturation is already high.

Technological confidence: a conditional enabler

Technological confidence significantly influenced financial feasibility but not adoption directly. This finding supports claims that perceptions of complexity and installation reliability are important—but not decisive—unless they impact expected financial outcomes. Consumers may accept technological uncertainty if cost savings are perceived to outweigh the risks. This partially aligns with studies like Balcombe et al. (2014), who found that technological trust can act as a moderating factor in low-carbon energy decisions.

Random Forest reinforcement and new insights

The Random Forest analysis validated the SEM findings, but also uncovered additional predictors such as homeownership and income, which are not latent constructs in the SEM. These structural variables are important access enablers: renters and low-income households remain systematically excluded, regardless of motivation or awareness. This finding aligns with broader socio-technical critiques that stress energy justice and distributional inequality in the transition to renewables (Sovacool et al., 2022). Space–time models like those of Copiello & Grillenzoni (2021) also highlight the geographic unevenness of solar deployment, echoing these findings.

Implications for practice and policy

The findings suggest that financial framing is essential for policy communication. Messaging around environmental or technological benefits may be insufficient unless accompanied by clear economic evidence, such as payback periods, rebates, and long-term savings. Programs targeting renters, such as virtual net metering or shared solar schemes, could help address access barriers identified in the RF model. Trust-building measures, such as installer accreditation and after-sales support, may also indirectly improve adoption by reducing perceived risk.

Limitations and future research

This study has several limitations that should be acknowledged. The cross-sectional survey design prevents definitive causal inference. Although the sample was representative of Queensland, findings may not generalise across all Australian states or internationally. Additionally, while the model explained a large

portion of variance in adoption intention, psychological factors such as environmental concern, trust in government, and risk aversion were not included and may offer further explanatory power.

Future research could adopt longitudinal designs to capture adoption over time, explore urban–rural differences and extend the SEM framework with cognitive or affective constructs. Hybrid models that integrate machine learning with behavioural theory could also improve predictive performance while maintaining interpretability.

CONCLUSION

This study examined the key determinants of residential solar PV adoption in Queensland using a Structural Equation Modelling (SEM) framework complemented by Random Forest (RF) analysis. The findings highlight the central mediating role of financial feasibility in shaping adoption decisions, with policy awareness, social influence, and technological confidence exerting indirect effects through this pathway. The alignment between SEM and RF results strengthens the argument that financial perceptions are the dominant mechanism by which households evaluate solar energy uptake.

The research contributes to solar adoption literature by demonstrating that even in a high-penetration market like Queensland, financial framing continues to outweigh normative or technological messaging. For policymakers, this suggests a continued need for transparent, accessible financial incentives and programs that lower entry barriers for low-income and rental households. For practitioners, ensuring trust and simplifying the customer journey remain key levers for expanding adoption.

Like all studies, this work has limitations. The cross-sectional design restricts causal inference, and the sample, while representative of Queensland, may not reflect national dynamics. Future research could explore longitudinal patterns of adoption, examine regional and rural differentiation and further develop hybrid modelling approaches that combine behavioural and machine learning frameworks. Expanding the model to include psychological constructs such as risk aversion or climate concern may also provide deeper insight into the solar decision-making process.

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