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The Role of Perceived Benefits, Installations, and Government Initiatives in Influencing Solar Energy Adoption Intentions at the Household Level in Jakarta

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ABSTRACT (10pt)

This study investigates the factors that influence the intention to adopt solar energy at the household level in Jakarta. As urban energy demands increase and environmental concerns intensify, renewable energy technologies, particularly solar power, offer a sustainable alternative. The research primarily focuses on three key drivers: perceived benefits, installation-related aspects, and the role of government initiatives. Using a structured survey questionnaire, data were gathered from residents across various housing areas in Jakarta. The questionnaire assessed respondents' awareness of renewable energy, perceptions of its advantages, perceived ease or complexity of installation, and the impact of governmental policies or incentives. The results of the analysis indicate that perceived benefits—such as long-term cost savings and environmental advantages—have a strong and statistically significant effect on adoption intentions. Government initiatives, including subsidies, public campaigns, and regulatory support, also play a critical role in shaping household decisions. Installation factors, although slightly less influential, still contribute meaningfully, particularly in terms of ease of access to reliable installation services and associated upfront costs. These findings highlight the importance of a multi-faceted approach to increasing residential solar energy adoption. Specifically, they underscore the need for government efforts to enhance public awareness and provide financial incentives, as well as the importance of ensuring accessible and user-friendly installation processes. The insights from this study can inform energy policymakers, private sector stakeholders, and urban planners in crafting effective strategies that support a greener and more sustainable urban energy landscape in Jakarta.

Keywords: solar energy adoption, perceived benefits, installations, government initiatives, adoption intention, housing, Jakarta.

INTRODUCTION

Indonesia is currently facing serious challenges in the energy sector, especially in urban areas such as Jakarta, which is characterized by increasing carbon emissions, accelerating urbanization, and growing energy demand that is still heavily dependent on fossil sources (IEA, 2019; Budiharto & Nugroho, 2019; Simamora & Harahap, 2019). From 1990 to 2018, carbon emissions in Indonesia increased by 313%, mostly contributed by the burning of coal, oil, and natural gas (WTE, 2021; Ministry of Energy and Mineral Resources, 2023). Dependence on fossil energy not only exacerbates the global climate crisis but also has a negative impact on air quality and public health in densely populated areas such as Jakarta (Laksmi & Rahmat, 2020; Purnomo & Murdapa, 2020).

On the other hand, energy consumption in the household sector shows a significant increasing trend, where between 2009 and 2018 household electricity consumption increased by 78.2% (PLN, 2019). Although the national electrification ratio reached 99.8% in 2023, most of the electricity supply still comes from fossil energy sources (Ministry of Energy and Mineral Resources, 2023; IEA, 2021). This shows that there is an urgent need to adopt alternative energy sources that are more environmentally friendly and sustainable (Nurdin & Setiawan, 2021; Astuti & Day, 2020).

As part of the national strategy, the Indonesian government has set a renewable energy mix target of 23% by 2025. One potential source of energy is solar energy, especially through the implementation of *Pembangkit Listrik Tenaga Surya* (PLTS) or Rooftop Solar Power Plants in the residential sector. Solar energy is considered to have great potential technically and geographically to meet household energy needs in a sustainable manner (Wulandari & Dewi, 2021; Oktaviani & Rachmawati, 2022). However, the adoption rate of this technology by urban communities, including in Jakarta, is still relatively low (Indriani & Pramudya, 2023; Dewanti & Sari, 2022). This suggests that there are structural and psychological barriers that need to be further identified.

Previous research has shown that the intention to adopt solar energy technology is influenced by various factors, both rational (such as cost efficiency and long-term benefits), social (subjective norms and environmental influences), and psychological (green consumption values and environmental awareness). In addition, facilitation conditions, performance perception, and adoption risk are also important determinants in adoption decisions (Ajzen, 2020; Bosnjak et al., 2020; Çoker & van der Linden, 2022; Sussman & Gifford, 2019; Yuriev et al., 2020). Therefore, a holistic approach is needed to understand the adoption behavior of this technology at the household level.

Based on these conditions, this study focuses on the identification and empirical analysis of various factors that affect the intention of household communities in Jakarta to adopt solar energy. By understanding these determinants, it is hoped that this research can contribute to the development of renewable energy technology adoption models that are not only locally relevant but also support national efforts in achieving an inclusive and sustainable energy transition.

Previous research has shown that solar energy is one of the most promising renewable energy sources in Indonesia, with the government's target to produce 6.5 GW of solar energy by 2025 and 45 GW by 2050. With this amount of potential, the development of *Pembangkit Listrik Tenaga Surya* (PLTS) technology in Indonesia can significantly help the country reduce its dependence on fossil fuels and contribute to achieving the government's renewable energy targets.

Geographically, Indonesia is located between 6° North Latitude to 11° South Latitude, so the country receives consistently high solar radiation throughout the year. Based on existing data, solar radiation levels in Indonesia average 4.8 to 5.4 kWh/m²/day in most areas. This radiation level greatly supports the development of solar power generation (PLTS) technology, especially for the residential, industrial, and commercial sectors.

Although the potential of solar energy in Indonesia is huge, its use has only reached 0.08% of the total existing potential, and the public still sees obstacles in terms of the initial cost of installing solar power plants (*Pembangkit Listrik Tenaga Surya*) (Katadata, 2021). One of the main obstacles is the lack of public understanding of the benefits of renewable energy. A survey showed that 19.7% of respondents admitted that low knowledge about renewable energy is a major obstacle in its development (Press Ministry of Energy and Mineral Resources, 2021). Only a small percentage of households have made use of solar panels, and many do not yet understand how this technology can help lower long-term electricity costs and support efforts to reduce carbon emissions.

Therefore, increasing awareness and education about renewable energy is very important to encourage the people of Jakarta to switch to cleaner and more sustainable energy. The government and related organizations need to continue to strengthen campaigns and provide adequate incentives for citizens to invest in solar energy technology (Koaksi Indonesia, 2022). Against the background of low utilization of solar energy in residential areas in Jakarta, this research focuses on exploring how the acceptance and adoption of solar energy in residential areas in Jakarta affect the acceptance and adoption of solar energy.

The purpose of this research is to determine the factors that affect the intention of adoption of solar energy in residential areas in Jakarta by reviewing several latent variables that can affect the interest in solar energy adoption. In addition, this research also aims to formulate strategies that can be used to increase the adoption intention of solar energy on a household scale.

METHOD

This research uses the Structural Equation Modelling (SEM) approach to analyze the data. SEM is a second-generation multivariate statistical analysis method that allows researchers to test relationships between variables simultaneously in a single integrated model. In SEM, latent constructs are measured through indicators that represent the variables being studied. The analysis process in SEM consists of two main stages: evaluation of measurement models and testing of structural models. This analysis is useful for evaluating the relationships between variables as a whole, providing a clearer picture of the relationships between the constructs in the research model.

In this research, the Partial Least Squares – Structural Equation Modelling (PLS-SEM) technique was applied to test the relationships between latent constructs in structural models. PLS-SEM, developed by Wold (1982), is used as a solution to the limitations of Covariance-Based SEM (CB-SEM), especially when the data used are non-normal or the sample sizes are small. PLS-SEM distinguishes between two types of indicators: reflective and formative (Chin, 1998). The Outer model is used to describe the relationship between constructs and indicators, as well as to evaluate the validity and reliability of measurements, while the Inner model describes the causal relationships between latent constructs in the model.

The evaluation process of the Outer model in PLS-SEM involves several important stages, namely indicator reliability tests, convergent validity, and discriminant validity. The validity of convergence is measured using Average Variance Extracted (AVE), which shows the extent to which the construct can explain the variance of its indicators (Hair et al., 2017). In addition, construct reliability is also measured using Cronbach's Alpha and Composite Reliability (CR), with values greater than 0.70 indicating acceptable feasibility. Discriminant validity evaluation is carried out using the Fornell-Larcker criteria and cross-loading analysis to ensure that the constructs do not conceptually overlap.

In the Inner model analysis stage, the causal relationships between latent constructs are tested using various statistical measures, such as the determination coefficient (R^2), effect size measure (f^2), and model fit test (SRMR). R^2 indicates how much variance of endogenous constructs can be explained by exogenous constructs in the model, while f^2 measures the magnitude of the influence of exogenous constructs on endogenous constructs. The model fit test was performed using SRMR, where an SRMR value of less than 0.08 indicates that the model has a good fit with the empirical data. The path coefficient is used to describe the direction and strength of the relationship between latent constructs, with significance tests carried out using the bootstrapping technique.

The data in this research is sourced from primary data collected through an online survey aimed at individuals who have or have the potential to adopt solar energy technology in the residential sector. The questionnaire covers various factors that can influence adoption decisions, such as *facility conditions*, government initiatives, awareness of renewable energy, moral norms, advantages of use, and aspects of technology installation. The results of the questionnaire are used as a basis for formulating hypotheses regarding the relationship between these factors. The number of samples in this study was determined using the purposive sampling method, assuming that the population is unknown, and respondents were selected based on the criteria of individuals aged at least 20 years living in residential areas in Jakarta, without gender or professional restrictions, so that the results reflect the diversity of views of the community. The questionnaire design was compiled based on conceptual models and observed variable indicators, covering eight variables with a total of 26 statements measured using a Likert scale of 1–5, as suggested by Hair et al. (2017), to provide clarity of interpretation and efficiency in the analysis. The research locations include five administrative regions of Jakarta (East, West, North, South, Central) as well as the *Kepulauan Seribu* (Thousand Islands), with the unit of analysis being individuals living in the region, both those who have used, have not used, or who have shown interest in solar energy.

RESULTS AND DISCUSSION

Evaluation of the Outer model (Measurement Model)

An evaluation of the outer model was carried out to assess the extent to which the indicator was able to represent the latent constructs measured in the model. In this research, the assessment of the outer model was carried out through testing aspects of validity and reliability. Validity serves to ensure that each indicator accurately measures the construct in question, while reliability aims to assess the consistency of measurements by the indicator. The outer model evaluation process includes testing convergent validity, discriminant validity, and overall construct reliability.

Convergent Validity & Reliability Test

The validity of the convergence is tested to ensure that the indicators measuring the same construct correlate well with each other. Convergent validity is assessed using loading factor and Average Variance Extracted (AVE) values. Meanwhile, reliability is assessed using Cronbach’s Alpha & Composite Reliability. The reliability and validity test of the outer model aims to ensure that each indicator in this research can represent its latent construct consistently and accurately. Based on the results of the analysis, all indicators have an outer loading value above 0.70, which is in the range of 0.804 to 0.946. According to Hair et al. (2017), an outer loading value above 0.70 indicates that the indicator has good convergent validity, so it can be declared valid in measuring the intended construct.

In the aspect of construct reliability, Cronbach's Alpha value for each variable is known to be above 0.70, meeting the criteria of good internal reliability as suggested by Hair et al. (2017). Specifically, the Intention to use variable has a Cronbach's Alpha value of 0.848, Attitude of 0.942, Facilitating conditions of 0.854, Government initiative of 0.862, Moral norms of 0.869, Awareness of 0.924, Perceived benefits of 0.910, and Installation of 0.855. These values indicate that the entire construct shows excellent internal consistency.

In addition, convergent validity testing is also carried out by looking at the Average Variance Extracted (AVE) value. The entire construct had an AVE value above 0.50, which suggests that more than 50% of the indicator's variance can be explained by the latent construct it measured (Hair et al., 2017). The AVE values of each construct are as follows: Intention to use is 0.768, Attitude is 0.852, Facilitating conditions is 0.774, Government initiative is 0.782, Moral norms are 0.788, Awareness is 0.868, Perceived benefits is 0.787, and Installation is 0.776. Based on these results, it can be concluded that all constructs in this research have met the required criteria of validity and reliability, making them suitable for use in further structural model analysis.

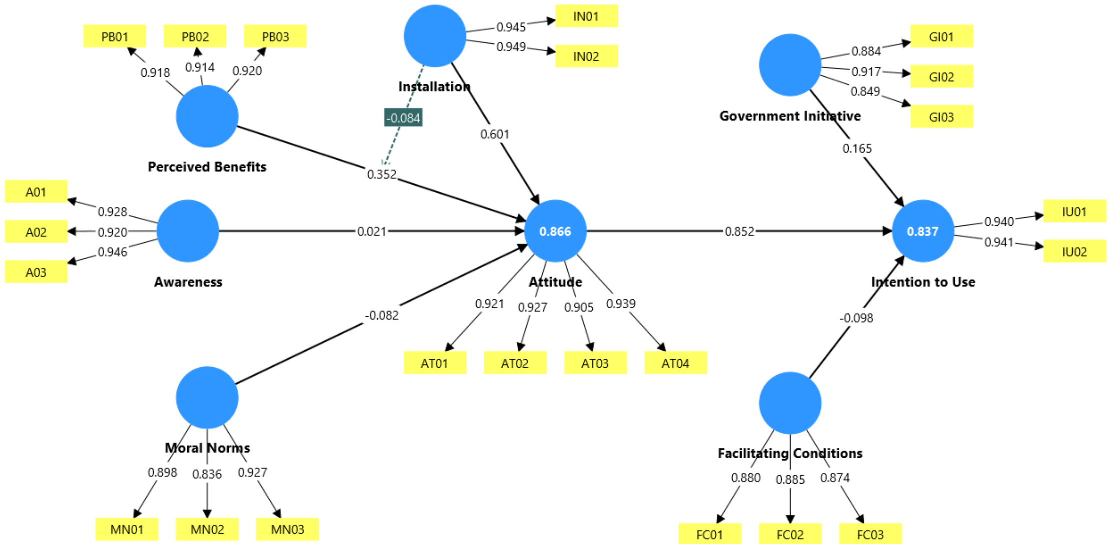

Figure 1. Models after Validity & Reliability test
Source: processed data

Overall, each indicator of each variable has an *outer loading* > 0.70 with an AVE value of > 0.5. so that all constructs used meet the criteria of convergent validity. Cronbach*'s previously calculated Alpha & Composite Reliability* also remained above the minimum limit of 0.70, indicating that the model's internal reliability and consistency were maintained. As a result, the updated model has better validity and reliability, with the remaining indicators still showing a strong contribution to the latent construct being measured. Thus, the model is ready to be used in major analyses to test relationships between latent variables in research.

Discriminating Validity Test

Discriminant validity aims to assess the extent to which a construct in a structural model can be clearly distinguished from other constructs. This means that a construct must not only be internally valid, but it must also demonstrate uniqueness that distinguishes it from other constructs in the model. Failure to meet the validity of the discriminant can lead to ambiguity in interpretation of the model's results, due to the possibility of overlap between constructs. Therefore, discriminant validity testing is an important step to maintain the integrity and accuracy of the structural model developed. In the context of PLS-SEM, discriminant validity is generally evaluated using several approaches, such as *Fornell-Larcker* criteria and *Cross-Loading analysis*.

Table 1. Analysis Results *Fornell-Larcker*

	A	AT	FC	GI	IN	IU	MN	PB
A	**0.931**	0.818	0.842	0.876	0.871	0.778	0.837	0.873
AT	0.818	**0.923**	0.753	0.806	0.915	0.912	0.649	0.861
FC	0.842	0.753	**0.880**	0.863	0.752	0.687	0.857	0.805
GI	0.876	0.806	0.863	**0.884**	0.828	0.767	0.828	0.846
IN	0.871	0.879	0.752	0.828	**0.947**	0.879	0.680	0.861
IU	0.778	0.873	0.687	0.767	0.879	**0.940**	0.582	0.780
MN	0.837	0.649	0.857	0.828	0.680	0.582	**0.888**	0.792
PB	0.873	0.861	0.805	0.846	0.861	0.780	0.792	**0.917**

Source: processed data

Based on the results of the analysis, all constructs in this model have met the Fornell-Larcker criteria. The square root value of AVE for each construct, which is shown in the diagonal value of the table, is higher than the correlation value between the other constructs. For example, construct A has an AVE square root of 0.931, which is greater than its highest correlation with other constructs of 0.876 for the GI construct. Similarly, the AT construct shows an AVE square root of 0.923, which is greater than its highest correlation with the IN construct of 0.915. The IN construct also showed good discriminant validity with the square root value of AVE of 0.947, greater than its highest correlation to the IU construct of 0.879. With the fulfilment of this criterion, it can be concluded that the constructs in the research model have a good level of discriminant validity. This shows that each construct is better able to explain the variance of its own indicators than the variance of other construct indicators (Fornell & Larcker, 1981; Hair et al., 2019). Thus, this model can be declared to have adequate construct validity, supporting the feasibility of further structural analysis.

Table 2. Results of Cross Loading *Analysis*

	A	AT	FC	GI	IN	IU	MN	PB	IN x PB
A01	0.928	0.763	0.783	0.814	0.832	0.725	0.801	0.816	-0.392
A02	0.92	0.706	0.774	0.789	0.773	0.671	0.767	0.775	-0.261
A03	0.946	0.811	0.796	0.843	0.827	0.772	0.771	0.846	-0.357
AT01	0.703	0.921	0.649	0.708	0.819	0.835	0.528	0.755	-0.444
AT02	0.7	0.927	0.662	0.702	0.802	0.845	0.568	0.769	-0.398
AT03	0.831	0.905	0.748	0.807	0.891	0.825	0.699	0.838	-0.554
AT04	0.782	0.939	0.718	0.755	0.863	0.861	0.597	0.814	-0.535
FC01	0.757	0.689	0.88	0.755	0.694	0.657	0.723	0.716	-0.31
FC02	0.724	0.635	0.885	0.762	0.632	0.582	0.76	0.706	-0.284

	A	AT	FC	GI	IN	IU	MN	PB	IN x PB
FC03	0.739	0.66	0.874	0.762	0.655	0.565	0.781	0.702	-0.302
GI01	0.766	0.635	0.767	0.884	0.663	0.616	0.764	0.721	-0.301
GI02	0.805	0.864	0.789	0.917	0.853	0.826	0.701	0.827	-0.485
GI03	0.751	0.578	0.732	0.849	0.636	0.533	0.755	0.668	-0.385
IN01	0.8	0.849	0.641	0.726	0.945	0.841	0.56	0.784	-0.425
IN02	0.85	0.883	0.781	0.84	0.949	0.825	0.724	0.847	-0.531
IU01	0.734	0.852	0.687	0.743	0.811	0.94	0.577	0.739	-0.43
IU02	0.729	0.862	0.605	0.7	0.842	0.941	0.517	0.729	-0.432
MN01	0.743	0.669	0.762	0.77	0.671	0.588	0.898	0.762	-0.33
MN02	0.671	0.378	0.706	0.632	0.408	0.322	0.836	0.55	-0.069
MN03	0.803	0.609	0.808	0.775	0.663	0.569	0.927	0.747	-0.268
PB01	0.781	0.775	0.723	0.754	0.769	0.686	0.755	0.918	-0.342
PB02	0.801	0.801	0.774	0.772	0.799	0.73	0.713	0.914	-0.379
PB03	0.82	0.793	0.716	0.801	0.801	0.729	0.711	0.92	-0.374
IN x PB	-0.364	-0.524	-0.34	-0.451	-0.506	-0.459	-0.277	-0.398	1

Source: processed data

The validity of the discriminant can also be tested using cross loadings analysis. According to Hair et al. (2019), the indicator must have a higher loading of the construct in question than loading of other constructs. In other words, the loading value of an indicator against its original construct must be greater than the loading of other constructs to ensure that the indicator empirically represents the construct being measured.

Based on the results of the analysis presented in Table 3, all indicators in this research show adequate discriminant validity. For example, indicator A01 has the highest loading on construct A of 0.928, which is higher than loading on other constructs such as AT (0.763), FC (0.783), and GI (0.814). Likewise, the AT01 indicator has the highest loading of 0.921 against the AT construct, which is much higher than the loading against other constructs such as A (0.703) and FC (0.649). This condition is consistent across all indicators tested, where each indicator always has the highest load against its original construct.

Overall, the results of this analysis reinforce the findings of discriminant validity that have been obtained through the previous Fornell-Larcker criteria. With the fulfilment of the criteria for discriminant validity through cross-loading analysis, it can be concluded that the constructs in this research model have met the measurement requirements required for model validity (Hair et al., 2019).

Evaluation *of Inner model* (Structural Model)

After the validity of the measurement (*outer model*) is ascertained, the next step in the analysis of the Partial Least Squares Structural Equation Modelling (PLS-SEM) model is to evaluate the *inner model*. The *internal evaluation of the model* aims to measure the structural relationships between latent constructs in the research model. According to Hair et al. (2019), the *evaluation of the inner model* includes testing several main criteria, namely the value of the determination coefficient (R^2), the value of the effect size ((f^2), the value of the significance of the path (through bootstrapping), and the relevant predictive value (Q^2).

Coefficient of Determination Test (R^2)

The test Coefficient of determination or R^2 value is used to measure how much variance of endogenous constructs can be explained by exogenous constructs in the model. The higher the R^2 value, the better the model is at explaining the variance that occurs. Hair et al. (2019) suggest that R^2 values of 0.75, 0.50, and 0.25 can be categorized as strong, moderate, and weak, respectively.

Tabel 3. Coefficient of Determination Test (R^2)

	R-square	R-square adjusted
AT	0.866	0.865
IU	0.837	0.835

Source: processed data

Based on the results of the analysis shown in Table 3, the AT (*Attitude*) construct has an R^2 value of 0.866, while the IU (*Intention to use*) construct has an R^2 value of 0.837. Both of these values are above the limit of 0.75, which according to Hair et al. (2019) indicates that the variance of these constructs can be explained substantially by the exogenous constructs in the model.

The adjusted R^2 value obtained is also very close to the R^2 value respectively, namely 0.865 for the AT construct and 0.835 for the IU construct. The small difference between R^2 and adjusted R^2 indicates that the model has a balanced complexity, so that the number of predictive constructs in the model is optimal and does not cause overfitting.

Thus, it can be concluded that this research model has a very strong predictive ability of the endogenous constructs studied. This strengthens the evidence that the structural relationships in the model are appropriate and reliable for further analysis processes.

Uji *Effect Size* (f^2)

In addition to evaluating the coefficient of determination (R^2) in the *inner model*, it is important to also assess the relative contribution of each exogenous construct to the endogenous construct individually. This is done through *effect size* (f^2) testing. According to Hair et al. (2019), the value of f^2 is used to see how much influence a particular exogenous construct has on the endogenous construct, after taking into account all the other constructs present in the model. Effect size testing is very useful for providing additional information beyond just statistical significance. A pathway may be statistically significant, but it has a small effect size, so practically its contribution to the model needs to be carefully considered (Hair et al., 2019).

Table 4. Analysis Results *Effect Size* (f^2)

Construct Relationships	**f^2**
AT → IU	1.503
FC → IU	0.014
GI → IU	0.033
IN → IU	0.417
MN → IU	0.013
PB → IU	0.161
IN x PB → IU	0.049
Construct Relationships	**f^2**

Construct Relationships	f^2
A → AT	0.000

Source: processed data

Based on the results shown in Table 4, it was found that the AT (*Attitude*) construct has a very large influence on the IU (*Intention to use*) construct, with a value of f^2 of 1.503. This value far exceeds the minimum limit of 0.35, indicating that AT is an exogenous construct that makes a dominant contribution in influencing the intention of use. Furthermore, the IN (*Installation*) construct also showed a large influence on the IU with an f^2 value of 0.417, which is also in the category of large effects. The PB (*Perceived benefit*) construct shows a moderate influence on IU with an f^2 value of 0.161. This indicates that PB has an important but not as big contribution as AT or IN in shaping usage intentions. Meanwhile, the GI (*Government initiative*) and IN x PB (interaction between *Installation* and *Perceived benefit*) constructs had f^2 values of 0.033 and 0.049, respectively, which were in the category of small effects. Construct FC (*Facilitating conditions*) and MN (*Moral norms*) show lower f^2 values, namely 0.014 and 0.013, so their contribution to IU is relatively small. In addition, the relationship between construct A (*Awareness*) to AT shows a value of f^2 of 0.000, which means that construct A does not contribute significantly to the variance of AT in this model. From the results of this evaluation, it can be concluded that in the developed research model, the AT and IN constructs are the key factors in influencing the intention of use (IU), while other constructs make a smaller but still relevant contribution to enrich the research model.

Relevant Predictive Test (Q^2).

In addition to evaluating the strength of structural relationships through the coefficient of determination (R^2) and effect size (f^2), it is also important to assess the model's ability to predict endogenous constructs. One method to test the predictive ability of a model is to use predictive relevance (Q^2) values. According to Hair et al. (2019), the Q^2 value is obtained through the blindfolding procedure and is used to assess how well the model is able to reproduce observational data related to endogenous constructs.

Table 5. Relevant Predictive Analysis Results (Q^2)

	Q^2predict
AT	0.858
IU	0.759

Source: processed data

In structural model testing using PLS-SEM, *predictive relevance* (Q^2) is an important indicator to assess the model's ability to predict new observational data. In SmartPLS 4, this test is performed through the PLS-Predict procedure, which automatically generates a Q^2 Predict value for the endogenous construct. According to Hair et al. (2022), the model is said to have good predictive ability if the Q^2 Predict value is greater than zero. Based on the results obtained (see Table 4.9), the AT (*Attitude*) construct has a Q^2 Predict value of 0.858, while the IU (*Intention to use*) construct has a Q^2 Predict value of 0.759. These two values are not only positive, but also indicate high numbers. This indicates that the model has a very strong predictive relevance to these constructs. In other words, the model is not only suitable for the data used in the estimation, but also has good predictive ability of new data. The high value of Q^2 Predict strengthens the validity of the *inner model* that has been tested previously through the determination coefficient (R^2) and effect size (f^2). Thus, it can be concluded that this research model has excellent predictive capabilities and is suitable for data-based decision-making.

Test Model Fit

In PLS-SEM, the assessment of the fit model is not the main goal, but rather a complement to increase confidence in the model's results. The main focus remains on the evaluation of *the outer model* (the validity and reliability of the construct) and *the inner model* (the relationship between constructs and predictive relevance).

Table 6. SRMR Analysis Results

	Value	Qualification
SRMR	0.064	< 0.08

Source: processed data

Based on the results of the evaluation, the SRMR value of this model is 0.064. This value is smaller than the maximum recommended limit, which is 0.08. This shows that the model developed in this research has a good fit, so that the structure of the relationship between the proposed constructs can represent empirical data with a minimal degree of inconsistency. With the fulfilment of the SRMR criteria, it can be concluded that the constructed structural model is feasible for use in further analysis, both in hypothesis testing and in the development of theoretical and practical implications.

Evaluation *of Path Coefficient* & Significance

One of the next crucial stages in the analysis is to evaluate the strength and significance of the relationships between variables in the model. This stage is known as path coefficient testing and statistical significance. The path coefficient serves to show the direction and magnitude of the influence of one construct on another construct in the model, while significance testing aims to ensure that the influence is statistically significant and not random. The closer the value of the +1 or -1 path coefficient is obtained, the stronger the relationship between independent constructs and dependent constructs. However, the path coefficient value that is considered acceptable also depends on the sample size and the complexity of the model. Hair et al. (2022) stated that the minimum acceptable path coefficient is in the range of 0.11 to 0.20, especially for the condition of a minimum sample count of 155 with a significance level of 5%. The significance of the relationship was tested through t-statistical values and p-values obtained from the bootstrapping technique. Decision-making on the hypothesis is carried out according to the following criteria:
If the p-value > 0.05 or the t-statistic < 1.96, then H_0 is accepted and H_a is rejected.
If the p-value < 0.05 or the t-statistic > 1.96, then H_0 is rejected and H_a is accepted.
If the p-value < 0.05 or the t-statistic > 1.96, then H_0 is rejected and H_a is accepted.

Direct Effect

The analysis of the direct influence in this research aims to find out and assess the extent to which independent variables directly affect dependent variables without going through mediation variables. The magnitude of this influence is assessed through the path coefficient value which describes the direction and strength of the relationship between constructs, as well as through testing the statistical significance using the bootstrapping method by paying attention to the t-statistic and p-value values. The interpretation of this direct influence is the main basis for testing the research hypothesis, as well as providing an initial overview of the role of each variable in the conceptual model that is constructed.

Table 7. Direct Effect

	Relationships Between Constructs	Original sample (O)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values	Information
H1	**PB -> AT**	0.352	0.056	6.313	0	Influential
H2	**A -> AT**	0.021	0.061	0.338	0.735	Not Influential
H3	**MN -> AT**	-0.082	0.044	1.86	0.063	Not Influential
H4	**IN x PB -> AT**	-0.084	0.02	4.315	0	Influential
H5	**IN -> AT**	0.601	0.064	9.348	0	Influential
H6	**AT -> IU**	0.852	0.037	22.824	0	Influential
H7	**FC -> IU**	-0.098	0.062	1.565	0.118	Not Influential
H8	**GI -> IU**	0.165	0.064	2.577	0.01	Influential

Source: processed data

The test results showed that *the perceived benefit* (PB) had a significant positive effect on *Attitude* (AT), with a path coefficient value of 0.352 and a p-value of 0.000. This indicates that the greater the benefit, the more positive the individual's attitude towards use. In contrast, *Awareness* (A) had no significant effect on *Attitude*, with a path coefficient of 0.021 and a p-value of 0.735, so the related hypothesis was not acceptable. Similarly, *Moral norms* (MN) did not have a significant effect on *Attitude*, although the t-statistic value was close to the significance limit, with a p-value of 0.063. In contrast, the interaction between *Installation* and *Perceived benefit* (IN x PB) had a negative but significant effect on *Attitude*, as shown by the path coefficient of -0.084 and p-value of 0.000. This shows that the interaction factor between innovation and perceived benefits can actually weaken positive attitudes towards use.

Furthermore, *Installation* (IN) directly exerts a strong positive influence on *Attitude*, with a path coefficient of 0.601 and a p-value of 0.000, confirming that innovation is an important factor in shaping attitudes. For the relationship to *Intention to use* (IU), the *Attitude* (AT) construct has a very strong and significant influence, with a path coefficient of 0.852 and a p-value of 0.000. These results show that positive attitudes are the main factor in forming the intention to use. In contrast, *Facilitating conditions* (FC) did not have a significant effect on *Intention to use*, with a p-value of 0.118. Meanwhile, *Government initiative* (GI) has a significant positive influence on *Intention to use*, with a path coefficient of 0.165 and a p-value of 0.010, which shows that government support plays an important role in encouraging intention to use. Overall, the results of this analysis support most of the hypotheses put forward in the study, with a primary focus on the role of *Attitude*, *Installation*, and *Perceived benefits* in shaping intent to use.

Indirect Effect

Table 8. Indirect Effect Evaluation Results

	Original sample (O)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values
A -> IU	0.018	0.052	0.337	0.736
IN -> IU	0.512	0.060	8.505	0.000

IN x PB -> IU	-0.072	0.017	4.278	0.000
MN -> IU	-0.070	0.038	1.861	0.063
PB -> IU	0.300	0.049	6.131	0.000

Source: processed data

Indirect influence testing aims to find out whether an independent variable can influence a dependent variable through a mediation construct. The results of the analysis of the indirect influence on this model show some important findings. First, the indirect effect of *Awareness* (A) on *Intention to use* (IU) was not significant, with a path coefficient value of 0.018 and a p-value of 0.736. This shows that *the Awareness* variable does not significantly affect the intention of use, either directly or through mediation constructs. In contrast, *Installation* (IN) has a strong and significant indirect influence on *Intention to use* (IU), with a path coefficient value of 0.512 and a p-value of 0.000. These results confirm that the installation factor has an important role in shaping the intention of use, either directly or through a mediation mechanism.

In addition, the interaction between Installation and Perceived benefit (IN x PB) showed a negative indirect effect on IU, with a path coefficient of -0.072 and a p-value of 0.000. Although the effect is significant, the direction of this negative relationship suggests that the combination of installation and perceived benefits can actually lower the intention of use in the context of this research. Meanwhile, the indirect influence of Moral norms (MN) on IU was not significant, with a path coefficient value of -0.070 and a p-value of 0.063. This shows that moral norms do not have a meaningful contribution to the intention of use indirectly through attitudes.

The perceived benefit (PB) showed a significant indirect influence on IU, with a path coefficient value of 0.300 and a p-value of 0.000. This means that the benefits felt by individuals are able to increase the intention to use through the mechanism of attitude influence. Overall, the results of this indirect influence analysis make it clear that the installation and perceived benefit factors are key elements that play a role in encouraging the intention of use, both through direct relationships and through the role of mediation.

Total Effect Evaluation

The total effect analysis aims to identify the overall influence exerted by independent constructs on dependent constructs, either through direct or indirect channels. The evaluation of the total effect provides a more complete picture of the strength of the relationship between constructs in the model.

Table 9. Total Effect Evaluation Results

	Original sample (O)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values
A -> AT	0.021	0.061	0.338	0.735
A -> IU	0.018	0.052	0.337	0.736
AT -> IU	0.852	0.037	22.824	0.000
FC -> IU	-0.098	0.062	1.565	0.118
GI -> IU	0.165	0.064	2.577	0.010
IN -> AT	0.601	0.064	9.348	0.000
IN -> IU	0.512	0.060	8.505	0.000
IN x PB -> AT	-0.084	0.020	4.315	0.000
IN x PB -> IU	-0.072	0.017	4.278	0.000
MN -> AT	-0.082	0.044	1.860	0.063
MN -> IU	-0.070	0.038	1.861	0.063
PB -> AT	0.352	0.056	6.313	0.000

PB -> IU	0.300	0.049	6.131	0.000

Source: processed data

Based on the results of the analysis, it was found that *Attitude* (AT) had the strongest influence on *Intention to use* (IU), with a total effect value of 0.852 and a p-value of 0.000. This confirms that attitude is a key factor in encouraging intent to use. Furthermore, *Installation* (IN) had a significant effect on both *Attitude* (with a value of 0.601) and Intention *to use* (0.512), both with a p-value of 0.000. This shows that the installation aspect is very important in forming a positive attitude and increasing the intention of use. *Perceived benefit* (PB) also showed a significant positive effect on both constructs, with a total effect value of 0.352 for AT and 0.300 for IU (p-value of 0.000 for both). This reinforces the role of perceived benefits in shaping attitudes and intentions of use.

However, the effect of *Awareness* (A) on *Attitude* (0.021; p-value 0.735) and *Intention to use* (0.018; p-value 0.736) was not significant, indicating that awareness in this study did not make a significant contribution to attitude or intention to use. For *Moral norms* (MN), the results showed a negative influence on AT (-0.082) and IU (-0.070), with a p-value of 0.063 each, so it can be concluded that the effect was not statistically significant. The *Facilitating conditions* (FC) for IU showed a negative relationship with a value of -0.098 and a p-value of 0.118, which was also insignificant. On the other hand, *Government initiative* (GI) has a significant positive influence on IU with a total effect value of 0.165 and a p-value of 0.010, showing the importance of the role of government support in encouraging use intention. In addition, the interaction between *Installation* and *Perceived benefit* (IN x PB) showed a negative effect on both *Attitude* (-0.084) and Intention *to use* (-0.072), but both were significant with a p-value of 0.000. This indicates that the combination of innovation with perceived benefits can actually reduce positive attitudes and intention to use. Overall, the total effect results make it clear that the *constructs of Attitude*, *Installation*, and *Perceived benefit* are the main factors that contribute the greatest in shaping intention to use, while other variables such as *Awareness* and *Moral norms* do not show significant contributions in this model.

Discussion

Hypothesis testing was carried out to assess whether the relationship between constructs in this research model is supported by empirical data. This hypothesis test uses a path coefficient and statistical significance evaluation approach based on t-statistical and p-value values obtained through bootstrapping techniques.

The following are the results of the hypothesis testing:

H1: Perceived benefit (PB) affects on Attitude (AT)

The results of the analysis showed that the perceived benefit had a positive and significant effect on Attitude, with a path coefficient of 0.352 and a p-value of 0.000. This means that H1 is accepted, indicating that the higher the perceived benefits, the more positive the individual's attitude.

H2: Awareness (A) has no effect on Attitude (AT)

The test results showed that the effect of Awareness on Attitude was not significant, with a path coefficient of 0.021 and a p-value of 0.735. Thus, H2 is rejected, signifying that the level of consciousness is not strong enough to form attitudes in this model.

H3: Moral norms (MN) have no effect on Attitude (AT)

This hypothesis showed insignificant results, with a coefficient value of -0.082 and a p-value of 0.063. Because the p-value > 0.05, H3 is rejected, so that moral norms do not have a significant effect on attitudes.

H4: Installation and Perceived benefit (IN x PB) interaction affects Attitude (AT)

The results showed that this relationship was significant with a path coefficient of -0.084 and a p-value of 0.000. Although the direction of the relationship is negative, H4 is accepted, indicating that the combination of installation factors and perceived benefits actually decreases positive attitudes.

H5: Installation (IN) affects Attitude (AT)

Installation has a strong positive influence on Attitude, with a coefficient of 0.601 and a p-value of 0.000. H5 is accepted, emphasizing that the installation factor plays an important role in shaping attitudes.

H6: Attitude (AT) affects Intention to use (IU)

Attitude showed a very strong and significant influence on Intention to use, with a path coefficient of 0.852 and a p-value of 0.000. With these results, H6 is accepted, supporting the importance of attitude as a key predictor in use intention.

H7: Facilitating conditions (FC) have no effect on Intention to use (IU)

Despite the negative relationship direction, Facilitating conditions had no significant effect on Intention to use, with a p-value of 0.118. Therefore, H7 was rejected, indicating that the facilitation conditions did not directly affect the intention of use.

H8: Government initiative (GI) affects Intention to use (IU)

The results showed that the Government initiative had a positive and significant effect on Intention to use, with a path coefficient of 0.165 and a p-value of 0.010. So that H8 was accepted, showing the importance of government support in increasing the intention to use.

CONCLUSION

The findings of this study provide several important insights into the factors influencing household adoption of solar energy in Jakarta. First, perceived benefits (PB) were found to have a positive and significant effect on user attitudes (AT), suggesting that the more users perceive tangible advantages, such as cost savings and environmental impact, the more favorable their attitudes become. However, both awareness (A) and moral norms (MN) did not significantly influence attitudes, indicating that while individuals may be informed or hold ethical values, these alone are insufficient to shape their attitudes toward solar energy adoption. Interestingly, the interaction between installation (IN) and perceived benefit (PB) had a negative and significant impact on attitude, revealing that when installation complexities coincide with high expectations of benefit, attitudes may be negatively affected. Despite this, installation (IN) independently exerted a positive and significant effect on attitude, affirming that ease of setup and successful implementation enhance users' perceptions. Furthermore, attitude (AT) emerged as the strongest predictor of intention to use (IU), underscoring its central role in the behavioral decision-making process. On the other hand, facilitating conditions (FC) did not significantly influence intention, suggesting that available support services or infrastructure are not yet sufficiently developed or recognized by users. Finally, government initiatives (GI) demonstrated a positive and significant influence on intention to use, highlighting the vital role of policy, incentives, and public campaigns in promoting adoption. Additionally, the model's predictive relevance (Q^2) confirmed its robustness in explaining endogenous constructs, and the SRMR value of 0.064 (< 0.08) indicated a good overall model fit. These findings imply that strategies to promote solar energy adoption should prioritize enhancing user attitudes through practical benefits and streamlined installations, while reinforcing governmental support to increase public commitment.

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