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The Impact of Brand Value Perception on Consumer Adoption Behavior of Distributed Energy Systems (DERs)

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Abstract. Consumer perceptions of brand value significantly influence the adoption of Distributed Energy Systems (DERs), a topic often overlooked due to insufficient information. This study investigates the impact of brand value perception on consumers' intention to adopt DERs using regression equations. It involves a comprehensive analysis considering factors like popularity and quality of service. Data was collected through structured surveys, and results indicated that higher consumer confidence and acceptance of DERs are directly linked to positive brand valuation. The SEM technique helped identify both direct and indirect consequences, revealing a strong relationship between brand value perception and DER adoption behavior, with a path coefficient of 0.65 and a p-value of less than 0.01. This statistically significant relationship underscores the critical role of brand perception in consumer behavior. Additionally, the model accounts for 54% of variations in customer acquisition behaviors, highlighting the importance that DERs place on their brand values. These findings provide valuable insights for enhancing consumer adoption strategies by emphasizing brand strength and trust in renewable energy solutions.

Key words. Brand Value Perception, Consumer Adoption Behavior, Distributed Energy Systems (DERs), Structured Equation Modeling (SEM), Sustainable Energy Solutions, Strategic Branding.

1. Introduction

Traditionally, power generation has been dominated by large, centralized power plants. There is a growing trend towards variable distributed energy generation, where energy conversion units are located near consumers, replacing very extended large units with smaller and decentralized ones [1]. DERs generation enables an individual buildings to be entirely needed self-sufficient in terms of electricity, heating, and cooling. This new and advancing concept has been successfully implemented in settings like hospitals, which is very needed for the highly reliable electricity supplies [2]. The idea of distributed energy generation is not new. Historically, before the advent of advanced technology and mass production, societies operated on decentralized systems [3]. For instance, homes in the far North used to rely on individual furnaces fueled by locally collected wood, due to poor transportation and traffic conditions. This period marked the 'first era of decentralization'. Currently, we live in a networked society often characterized by globalization and urbanization, where social structures revolve around production and consumption [4]. Yet, a shift towards a 'second era of decentralization' is emerging, driven by different motivations. On one hand, decentralization addresses the vulnerabilities of complex systems; on the other, it promotes economic democracy and the redistribution of power [5].

Distributed energy systems are particularly beneficial in large, sparsely populated countries like Canada and Russia, where these systems are likely to be adopted first [7]. In the future, many district heating plants may be replaced by units that generate both heat and electricity [6]. Nordic countries, where district heating is a significant source of heat, show the greatest potential for this transition [8]. For example, in 2002, district heating accounted for 48% of Finland's heating energy, a figure that was similar in other Nordic countries. A DERs offers an self efficient, improved reliable, and friendly alternatives to the variable traditional energy systems [9]. The need of new solutions often makes an impact on decision-making processes. There is a major factor positive attitude makes sustainable development in political definitions and among individual property owners [10].

2. Literature Review

A. Review on Distributed Energy Systems

Moafi et al. [11] investigated the impact of the very evolution of electricity markets over recent decades, emphasizing strategies to reduce costs and need to enhance the improved profits through cooperative structured frameworks among the various electricity manufacturers. Their study introduces a three-level gameplay-based intelligent structure for evaluating the individual and collaborative strategies of the organizations. At Level I, particle swarm optimization (PSO) optimizes the various distributed energy resource (DER) deployment to maximize profits, accounting for network constraints. Level II employs fuzzy logic to classify DERs into groups ensuring fairness, considering the intermittent nature of renewable sources and load demands.

Zografopoulos et al. [12] investigated the issues and troubles of cyber security posed by distributed energy resources (DERs) in electric power grids of the sectors, emphasizing the impact of the vulnerabilities at both cyber and physical layers. They highlighted the diverse architectural dependencies and communication protocols of DERs, underscoring their vital impact of the potential to widen the threat landscape and compromise grid resilience. The study has a vital impact of addressing the research gaps in existing research by analysing adversarial capabilities and currently presenting displacing the mitigation strategies to safeguard against cyber-attacks on mission-critical DER assets.

Sang et al. [13] investigated the impact of increasing distributed energy resources (DERs) on power system frequency stability. They proposed a CSNN-embedded FCUC framework to improve the whole system's reliability.

Zhang et al. [14] investigated the development of super hydrophobic methylated cellulosic turboelectric materials of varying the need for energy harvesting. Enhancing the hydrophobicity of cellulose Nano fibrils (CNF) using silica micro nanoparticles, achieving a hybrid and enhanced water contact angle (WCA) of 154.7 ° and constant surface roughness (RMS) of 72.61. Researchers designed a rectangular TENG with an internal fixed grid structure, a constant excellent electrical output (120 V) and cycling stability (10,000 cycles) for distributed energy harvesting applications.

Ghiasi, et al. [15] investigated the need of evolution of smart grids (SG) alongside with the integration of Internet of Energy (IoE) systems. Research investigated the stresses of the need for mathematical modelling and real-time simulations to assess IoE's impact need of reducing CO_2 emissions, addressing the need for potential in achieving low-carbon sustainable energy development.

B. Review of Brand Value Perception

Leite et al. [16] conducted a detailed comprehensive analysis of varying the brand valuation impact rankings, Examining the 107 global brands industry across the several industry categories from 2016 to 2021, the research study revealed significant variability in brand value estimations, attributed to differences in methodologies, particularly in measuring brand equity.

Sánchez-Iglesias et al. [17] investigated the influence of a company's financial performance and reputation on customer values perception and engagements, using data from several automotive companies over a period of 2010-2018. Research work signifies the weighted least squares for panel data analysis and found that firm value and corporate reputation significantly impact customer engagement. Research work enriches the field of customer engagement by integrating insights from employees and customers in an international context.

Llorente-Barroso et al. [18] discuss the increasing prominence of aging and disability in developed societies, highlighting initiatives aimed at strengthening corporate and institutional commitment to the inclusion of vulnerable adults.

Amani et al. [19] explored the mechanisms of value co-creation from the perspective of local residents in the tourism sector. They adopted a resident-centered dominant logic to develop and test a research model that examined the relationship between tourism ethnocentrism, residents' support for tourism, and the co-creation of destination brand value. Using data collected from 357 local residents in Dodoma City, Tanzania, and analyzed through structural equation modeling, the study found a positive relationship between tourism ethnocentrism and residents' support for tourism, with residents' support mediating the effect on destination brand value co-creation.

Duan et al. [20] investigate the impact of digital empowerment on brand value using panel data from China's top 500 companies, 2011-2020. Deploying fixed-effect panel data models and chain mediation models to analyse the digital empowerment and the impact of the enterprises through consumption upgrading, concepts, and patterns.

3. Proposed Methodology

The urgent analysis of impact of brand value perceptions on worldwide consumer adoption behaviours of distributed energy systems (DERs) starts with defining the research design, focused on understanding the consumer perceptions of brand value influence their decisions regarding DER adoption. A detailed literature review follows, showing the current studies on consumer behaviour patterns, good and positive brand perception, and urgent adoption of energy systems. DERs Systems Data collection consists of gathering consumer feedback through surveys and interviews to consider their brand perceptions of enhanced brand value in relation to DERs. Sampling techniques are very vital to selecting a representative group of important consumers who have vast experience or interest in implementing the DERs. Analysis such as Qualitative and quantitative data methods are then applied to interpreting the consumer response and identifying the pattern in brand perception of brands makes a huge impact on adoption behaviour. Creating a Model development may be needed to illustrate relationship between perception of brand value and adoption behaviors, providing a detailed framework for validations through very rigorous tests and analysis. Conclusion drawn from the study highlights the significant roles of brand value perception in needed for shaping consumer decisions on DER adoption, with selective implications for marketing strategies and policy recommendations in promoting sustainable energy solutions. The analysis discusses the improving the brand value perceptions can improve the number of consumer acceptances and uptakes of DER technologies (Figure 1).

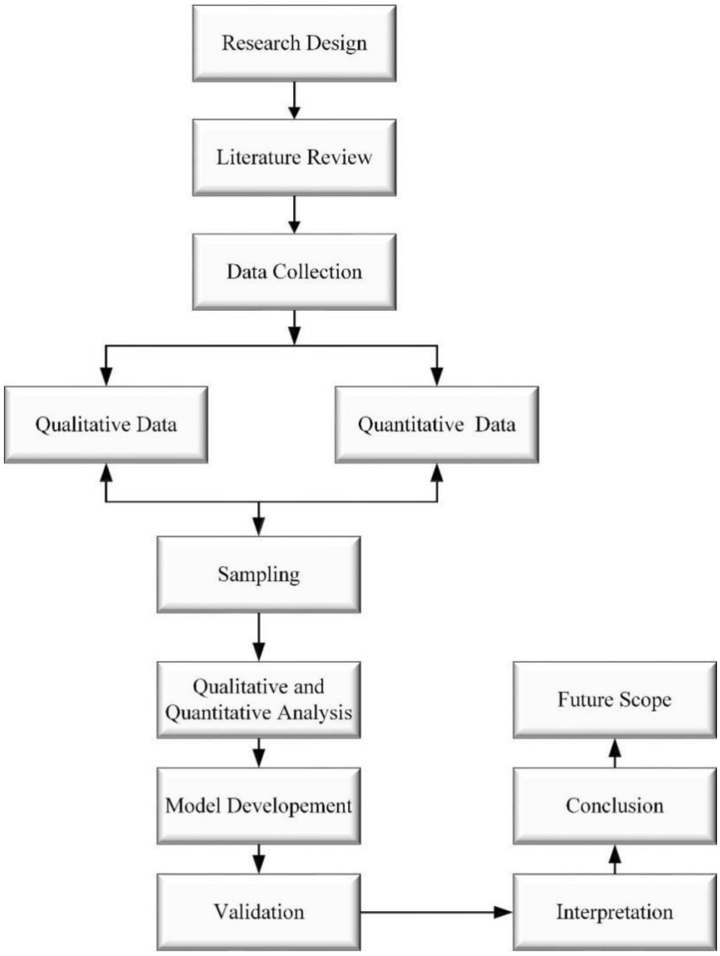

Figure 1. Proposed Methodology Workflow

A. Classification of Distributed Energy Systems

In Figure 2, DES can be classified based on several key factors. Initially deployment of grid connection status classifies the between Grid-Tied (GT) DES, which is combined with the multiple electrical grid and can supply excess amount of power back to it, exemplified by solar rooftop PV systems. While compared to the Off-Grid (DG), DES operates independently of the grids DES can be classified by their usage and application scope. Small Buildings and industrial applications DES caters the residences by meeting their electricity needs, typically through the needed variable systems like commercial and needed solar PV setups. District Level DES serves the classifying clusters of buildings such as neighbourhood or needed commercial districts, deployment of small-scale wind farms combined with the integration of the solar PV systems.

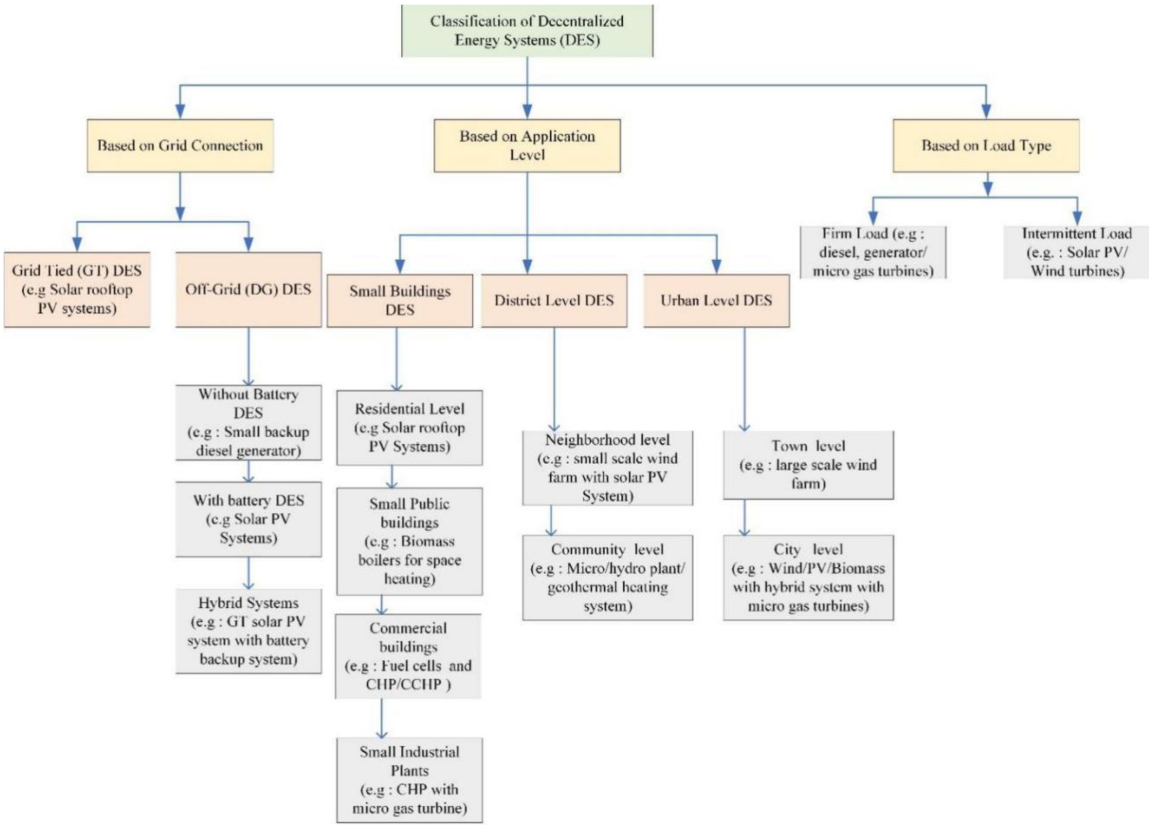

Figure 2. Classification of DERs

Connection with the urban Level DES is set up for larger urban areas and needs the usage of complex setups like several setups like large-scale wind farms integrated with micro gas turbines. Finally, DES can also be classified by the type of variable electrical load they serve. Distributed and classified Firm Load DES provide consistent and constant steady electricity demand, met by technologies like fuel supplying systems and power supply diesel generators or micro gas turbines. Intermittent Load DES cater to variable electrical demands that fluctuate with availability and addresses the energy needs, commonly classified by solar PV or wind turbine system.

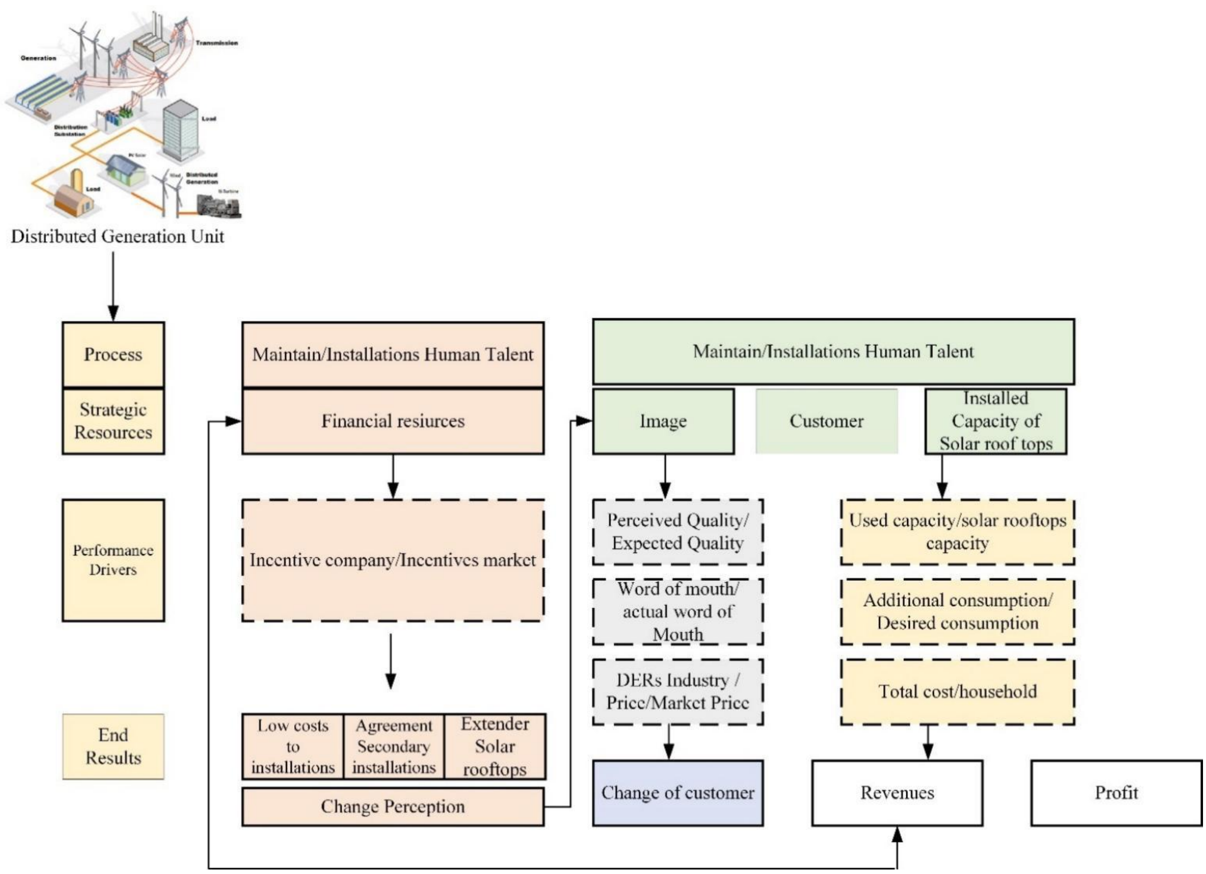

Figure 3. Architecture of Integration of Brand Value with Distributed Energy Systems

Figure 3 depicts comprehensive process diagrams depicting the various factors that influence brand value perception in DERs. The classified block diagram categorizes these factors into various key sections. Under the several Performance Drivers, factors such as the expertise of the installation and maintenance workforce, enhanced strategic resource management, and constant financial stability are highlighted. These elements collectively dominate a positive brand image by ensuring variable and trustworthy reliable and efficient DER systems. The diagram also makes sure the importance of versus Expected Quality in the manufactured product, where meeting the client is needed to ensure the quality or exceeding customer expectations which leads to slight disappointment of DER performance can improve the brand perceptions significantly. The Price dynamics are another much needed important factor to consider, demonstrating the competitive environment within the DER industries can have a major influence on the brand value perception. The Final Results section underscores need for lower setup and installation costs and increased revenue generation through DERs on brand perception. Factors like critical positive aspects such as word-of-mouth and changes in customer consumption behaviours due to DER adoption play critical roles in creating overall customer perception of DER brands, the concept stresses the iterative complex interaction between these factors and signifies the vital need of strategic importance for DER companies to focus on qualities, pricing, customer satisfaction, and market competitiveness to enhance their brand value perception effectively.

4. Research Methodology

Utilizing a quantitative research methodology, data was gathered from 227 participants in the region of China, specifically targeting individuals with experience using Distributed Energy Resources (DERs). The collected data was analyzed using the Structural Equation Modelling (SEM) technique and Multiple Regression Analysis (MRA) with the SPSS AMOS software.

A. *Research Design*

The research utilises a quantitative design approach to investigate the factors which influence brand value perception of DERs of that usage group. This study utilizes primary and secondary data sources, gathering information from reputable journals, newspapers, websites, and conducting e-mail surveys with self-administered questionnaires during direct interactions with young respondents in China. Samples were selected from the southern region of China, focusing on user groups that are in need of usage of DERs. The data was collected from 227 sample respondents. The questionnaire, comprising 15 items, was developed after an exhaustive review of secondary sources, and primary data collection involved distributing email surveys to users focused on DERs.

B. *Research Measurement*

As shown in Figure 4, the study adopts Rakib et al.'s (2022) model to explore the factors that influence DERs brand image. The survey questions employ a Likert scale, where respondents rate their agreement on a range of 1-5. It is given in Table 1. Here, 1 denotes "(SD) Strongly Disagree", and 5 represents "(SA) Strongly Agree". Intermediate values on the scale indicate varying degrees of disagreement or agreement, with higher code values reflecting greater agreement. Research instruments which are taken for this study, are highlighted in Table 2.

Table 1. Likert Scale Score

WEIGHT OF THE SCORE	1	2	3	4	5
INSTRUMENT CATEGORY	Strongly disagree	Disagree	Neutral	Agree	Strongly agree

Table 2. Research Instrument

VARIABLES	QUESTIONNAIRE	ITEM CODE	REFERENCES
Purchase intention	I have a strong intention to buy products or services in the future. [DERs]	Purchase intention 1	Salhab et al. (2023) [27]
	I would highly recommend this company to others.[Consumer to service providers]	Purchase intention 2	
	I prefer to buy this product or service over those from any other company.	Purchase intention 3	
Brand image	The supply of electricity from Nano sponge brand is really well done	Brand image 1	
	The services a trustworthy and work really well.	Brand image 2	
	The supply of power and transmission is as good	Brand image 3	
Product features	When purchasing an energy-related system, I take the safety into consideration.	Pro feat 1	Rakib et al. (2022) [28]
	I opt for a DERs with a low price option.	Pro feat 2	
	I take into account the transmission capacity of the DERs.	Pro feat 3	
Social influence	My friends consistently encourage me to purchase the DERs as theirs.	Social influence 1	
	I typically seek advice from industrial people when deciding on a DERs to consideration.	Social influence 2	
	People expect the uninterrupted power supply for the usage.	Social influence 3	
Product price	Purchasing DERs from international firms' selling platforms might incur higher costs compared to local marketplaces.	Pro price 1	N'da et al. (2023) [29]
	It's possible to secure better discounts when purchasing DERs from local marketplaces compared to international firms.	Pro price 2	
	I'm likely to save more money by purchasing DERs from local marketplaces rather than from international firms.	Pro price 3	

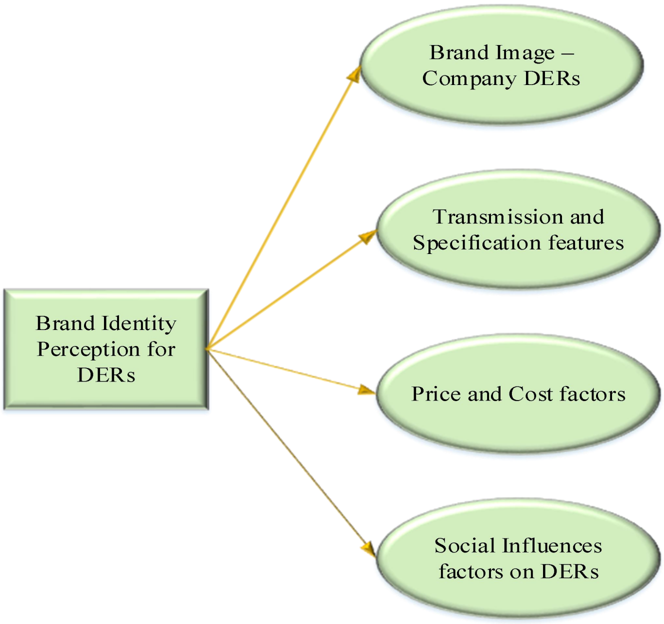

Figure 4. Adapted Hypothesized Hodel from Rakib et al.'s (2022) [28]

1) Data Analysis

To evaluate the data, descriptive and multivariate analyses are employed in this research, including Confirmatory Factor Analysis (CFA), reliability analysis, SEM, multiple regression analysis and moderation analysis. The data processing is assisted by utilizing IBM SPSS and AMOS software and fit indices of the proposed model and hypothesis are evaluated.

5. Results and Discussions

This study used IBM, SPSS, and AMOS tool to analyse the data and it is used to measure the validity of the questionnaire. After the validity and reliability of the questionnaire. After the validation of validity and reliability hypothesis testing was carried out to analyse the relationships between variables. SEM approach was utilized to test the hypothesis.

A. Evaluation of Reliability and Validity Measures

In terms of reliability analysis, Cronbach's Alpha (α) is utilized to determine the internal consistency of every latent variables. α (CA) shows the strong relationship of linked variables in the construct. It is categorized as $\alpha <$ 0.50 is rejected, $0.50 \leq \alpha < 0.60$ is poor, $0.60 \leq \alpha < 0.70$ is suitable, $0.70 \leq \alpha < 0.90$ is good and $\alpha \geq 0.90$ is excellent [22]. In the measurement model, each construct's reliability is calculated by Composite Reliability (CR). It is recommended that the CR should be higher than 0.70 and CR should be higher than the model's AVE (Average Variance Extracted) value [29]. In terms of discriminant validity, AVE value should be higher than 0.70 and should be higher than inter-construct correlations.

1) Test of Reliability

The findings from the reliability analysis suggest that the measured items demonstrate a strong consistency, as reflected by a value of 0.877. A value which is above 0.70 is generally considered reliable, and in this case, the result of 0.877 suggests a brand value of DERs robust reliability, indications from the Industrial sectors reliability analysis suggest that the items, when considered together, form a dependable and internally cohesive scale or measure [21]. In this research, CR value of 83.190 for all constructs is greater than recommended value, which ensures the internal consistency of all constructs. Furthermore, this value is greater than the AVE of 27.54, indicating the presence of convergent validity. Table 3 shows the factor loadings for every variable, indicating that all loadings are above 0.50.

Table 3. Factor Loadings of Each Construct and Descriptive Statistics

CONSTRUCTS	FACTOR LOADINGS	STD. DEVIATION	MEAN
PI1	0.821	1.1370	3.64
PI2	0.969	1.2371	4.63
PI3	0.9736	1.4385	1.6 5
BI1	0.9341	1.5420	3.31
BI2	0.9276	1.2481	3.63
BI3	0.9853	1.4415	4.52
PF1	0.9752	1.2393	5.36
PF2	0.9843	1.2455	6.52
PF3	0.9476	1.5358	7.33
SI1	0.9752	1.5311	2.35
SI2	0.9455	0.9658	1.52

CONSTRUCTS	FACTOR LOADINGS	STD. DEVIATION	MEAN
SI3	0.9143	1.4637	3.71
PP1	0.9830	1.7524	2.52
PP2	0.7956	1.3048	1.74
PP3	0.9676	1.324	3.8

2) *Test of Validity*

All variables in this research are found to have Average Variance Extracted (AVE) values which is more than 0.50, indicating strong having a discriminant validity according to established variable criteria [22]. Moreover, the AVE values surpassed the MSV to ensure discriminant validity, and the square roots of the AVE values exceeded the inter-construct correlations. Thus, all constructs in this research successfully achieve the criteria for ensuring discriminant validity. The value of AVE (27.54), shows that the correlation between dimensions was less amount than the root of the AVE for each dimension. Table 4 indicates that the measure has sensible discriminant validity.

Table 4. Measurement of Validity and Reliability

CONSTRUCTS	CRONBACH'S ALPHA	CR	AVE
Purchase intentions	0.984	76.81	28.54
Social influences	0.974	81.19	28.54
Product feature	0.934	76.77	28.54
Product price	0.914	77.44	28.54
Brand images	0.974	78.81	71.3

B. *Model's Fit Evaluation*

Process macro-SPSS AMOS is utilized to conduct CFA (Confirmatory Factor Analysis) with the sample size of 227. The model's suitability was measured using numerous fit indices, including the CFI (Comparative Fit Index), GFI (Goodness of Fit Index), and AGFI (Adjusted Goodness of Fit Index) [23]. According to established guidelines, the normed chi-square/df (Chi-square Index) should be below 3, while the Normed Fit Index (NFI) and Incremental Fit Index (IFI) should exceed 0.9. Also, the Parsimony-adjusted Normed Fit Index (PNFI) and Parsimony-adjusted Comparative Fit Index (PCFI) should both surpass 0.5. Lastly, the Root Mean Square Error of Approximation (RMSEA) should be under 0.08 to assess the model's suitability. To evaluate the hypotheses, SEM technique has been utilized. The model fit indices are checked before evaluating hypotheses. To evaluate the overall model, various fit indices are represented in Table 5.

Table 5 represents the GFI value of 0.974, which is lower than the acceptable level. Thus, this model has a good fit with satisfied values. The RMSEA value of 0.137, which is lower than the acceptable level of 0.80. The AGFI value of 0.868 is more than the recommended value of 0.8. GFI, IFI, CFI and NFI attain higher values than the acceptable level of 0.9. Thus, the model fit indices evaluated in this research show the suggested range of suitability standards. Consequently, it seems to be reasonable to perform the analysis of the outcome of the structural model.

Table 5. Model Fit Indices (CFA)

METRICS	RECOMMENDED LEVEL [32-36]	VALUE OF THE MODEL	RESULT
GFI	>.8	0.964	Good
AGFI	>.9	0.848	Good
IFI	>.8	0.986	Good
CFI	>.8	0.916	Good
RMSEA	<.9	0.127	Good
NFI	>.7	0.985	Good

C. *Multiple Regression Analysis to Test the Developed Hypothesis*

SEM and Maximum Likelihood (ML) techniques were assessed to test the hypothesis utilizing SPSS AMOS, version 24, to analyse the latent variables in the fundamental structure of the model.

Table 6: Model Summary of MRA

TECHNIQUE	R SQUARE	ADJUSTED R SQUARE	R	ESTIMATE'S STD. ERROR
1	0.523	0.485	.724a	0.68572
a Predictors: (Constant), BRAND IMG 3, PRO FEAT 1, PRO PRICE 1, SOCIAL INFLU 2, SOCIAL INFLU 3, PRO PRICE 2, BRAND IMG 1, PRO PRICE 3, SOCIAL INFLU 1, PRO FEAT 3, BRAND IMG 2, PRO FEAT 2				

Table 6 depicts the multiple variable regression analysis and provides valuable insights into the relationship between the DVs (Dependent Variable), Purchase Intention of DERs, and a set of IVs, including PRO FEAT 1 2 and 3, PRO PRICE 1, 2 and 3, SOCIAL INFLU 1, 2 and 3, BRAND IMG 1, 2, and 3. The model summary shows that the overall model is statistically significant (F (11, 215) = 37.84, p < 0.001), explaining an increased substantial proportion of the variance in Purchase Intention (R Square = 0.522). The variable of R Square (0.495) considers the number of predictors and suggests that approximately 49.5% of the changeability in purchase intention is explained by the included variables [24]. The standard errors of the need of estimate (0.67592) reflect the accuracy of the model in predicting Purchase Intention. The variable individual of the predictors contributing to the model include BRAND IMG]3, PRO FEAT 1, PRO PRICE 1, SOCIAL INFLU 2, SOCIAL INFLU 3, PRO PRICE 2, BRAND IMG 1, PRO PRICE 3, SOCIAL INFLU 1, PRO FEAT 3, BRAND IMG 2, and PRO FEAT 2 (constant term included).

Table 7. ANOVA Results of Multiple Regression Analysis

ANOVA						
TECHNIQUE		MEAN SQUARE	SIG.	F	DF	SUM OF SQUARES
1	Regression	7.812	0.000	18.421	13	107.582
	Residual	0.467			234	98.77
	Total				236	216.34
a DV: PURCHASE_INTENSION						
b Predictors: (Constant), BRAND IMG 3, PRO FEAT 1, PRO PRICE 1, SOCIAL INFLU 2, SOCIAL INFLU 3, PRO PRICE 2, BRAND IMG 1, PRO PRICE 3, SOCIAL INFLU 1, PRO FEAT 3, BRAND IMG 2, PRO FEAT 2						

Table 7 reveals the analysis of variance (ANOVA) for the multiple regression model with Purchase Intention as the DV and PRO FEAT 1, 2 and 3, PRO PRICE 1, 2 and 3, SOCIAL INFLU 1, 2 and 3, BRAND IMG 1, 2 and 3 as independent variables indicates a significant overall model fit (F(12, 214) = 19.441, p < 0.001). The mean square for the regression (8.882) reflects the average variability explained by the model for each degree of freedom. The regression model explains a substantial amount of variability in purchase intention, as evidenced by the significant F-statistic. The regression sum of squares (106.582) is significantly greater than the residual sum of squares (97.770), supporting the notion that the integration of the IVs contributes to the prediction of Purchase Intention.

Table 8. MRA Coefficient Results

COEFFICIENTS						
Technique	Variables	Standardized Coefficients	Unstandardized Coefficients	Sig.	T	Std. Error
		Beta	β			0.239
1	(Constant)		-0.021	0.929	-0.090	0.124
	PRO FEAT 1	0.196	0.178	0.154	1.432	0.123
	PRO FEAT 2	0.083	0.075	0.546	0.604	0.06
	PRO FEAT 3	0.028	0.025	0.672	0.424	0.048
	PRO PRICE 1	0.112	0.094	0.05	1.967	0.052
	PRO PRICE 2	0.086	0.077	0.141	1.476	0.048
	PRO PRICE 3	0.162	0.134	0.006	2.768	0.055

COEFFICIENTS						
Technique	Variables	Standardized Coefficients	Unstandardized Coefficients	Sig.	T	Std. Error
	SOCIAL INFLU 1	0.065	0.060	0.275	1.094	0.05
	SOCIAL INFLU 2	0.143	0.128	0.012	2.548	0.05
	SOCIAL INFLU 3	-0.107	-0.101	0.047	-1.999	0.055
	BRAND IMG 1	0.241	0.237	0.000	4.274	0.116
	BRAND IMG 2	0.113	0.096	0.405	0.834	0.119
	BRAND IMG 3	-0.007	-0.007	0.956	-0.055	
a DV: PURCHASE_INTENSION						

Table 8 shows the multiple regression analysis of coefficients provides insights into the relationships between the DV, Purchase Intention, and the IVs (PRO FEAT 1, 2 and 3, PRO PRICE 1, 2 and 3, SOCIAL INFLU 1, 2 and 3, BRAND IMG 1, 2 and 3). The intercept (constant) is not statistically noteworthy (β = -0.021, p = 0.929), signifying that when all independent variables are zero, the predicted Purchase Intention is not significantly different from zero.

Among the predictors, PRO FEAT 1 (β = 0.178, p = 0.154), PRO FEAT 2 (β = 0.075, p = 0.546), and PRO FEAT 3 (β = 0.025, p = 0.672) are not statistically remarkable, suggesting that the coefficients for these variables are not significantly different from zero. PRO PRICE 1 (β = 0.094, p = 0.05), PRO PRICE 2 (β = 0.077, p = 0.141), and PRO PRICE 3 (β = 0.134, p = 0.006) show significant positive relationships with Purchase Intention. This implies that an increase in perceived product prices is associated with a higher Purchase Intention, and the p-values suggest that PRO PRICE 1 and PRO PRICE 3 are particularly influential [25].

Among the social influence variables, SOCIAL INFLU 1 (β = 0.06, p = 0.275) is not statistically significant, while SOCIAL INFLU 2 (β = 0.128, p = 0.012) has a positive effect on buying intention. On the other hand, SOCIAL INFLU 3 (β = -0.101, p = 0.047) has a significant negative effect, indicating that higher levels of SOCIAL INFLU 3 are associated with lower Purchase Intention.

Among the brand image variables, BRAND IMG1 (β = 0.237, p < 0.001) has a highly significant positive effect on Purchase Intention, suggesting that a positive brand image leads to increased purchase intentions. BRAND IMG 2 (β = 0.096, p = 0.405) and BRAND IMG3 (β = -0.007, p = 0.956) are very not statistically significant.

Table 9. Results ANOVA of Gender and Factors of Brand Identity Perception

ANOVA TEST						
		Total of Squared Values	df	Mean Squared Values	f	Sig.
PRO FEAT 1	Between Groups	5.748	2	6.747	5.91	0.122
	Within Groups	241.235	233	1.186		
	Total	248.982	225			
PRO FEAT 2	Between Groups	0.617	2	0.626	0.557	0.47
	Within Groups	252.34	224	1.137		
	Total	253	225			
PRO FEAT 3	Between Groups	1.004	2	1.004	0.884	0.355
	Within Groups	251.129	243	1.142		
	Total	253.12	244			
PRO PRICE 1	Between Groups	3.129	2	2.129	1.805	0.293
	Within Groups	287.406	233	1.384		
	Total	289.596	234			
PRO PRICE 2	Between Groups	0.786	2	0.786	0.722	0.5
	Within Groups	248.204	224	1.119		
	Total	251	226			
PRO PRICE 3	Between Groups	0.039	2	0.048	0.039	0.876
	Within Groups	297.076	243	1.327		
	Total	297.126	234			
SOCIAL INFLU 1	Between Groups	0.305	2	0.305	0.293	0.761
	Within Groups	237.71	233	1.071		
	Total	235.916	225			
SOCIAL INFLU 2	Between Groups	4.11	2	4.51	3.812	0.059
	Within Groups	252.35	233	1.133		
	Total	256.76	234			
SOCIAL INFLU 3	Between Groups	0.392	2	0.399	0.389	0.549
	Within Groups	225.54	224	1.017		
	Total	225.916	234			
BRAND IMG 1	Between Groups	4.121	2	4.821	5.311	0.013
	Within Groups	207.30	224	0.926		
	Total	212.129	225			
BRAND IMG 2	Between Groups	6.123	2	6.133	5.042	0.026
	Within Groups	271.227	223	1.216		
	Total	277.36	224			
BRAND IMG 3	Between Groups	1.317	2	1.217	1.247	0.385
	Within Groups	257.238	243	1.149		
	Total	258.516	214			

Table 9 denotes that an ANOVA was conducted to examine the influence of variable gender on respondents' perceptions of across the various independent variables of the DERs, social influences of the (SOCIAL INFLU1, SOCIAL INFLU2, SOCIAL INFLU3), and variable brand images (BRAND IMG 1, BRAND IMG 2, BRAND IMG 3). No significant industrial differences were found in the responses to PRO FEAT 2, PRO FEAT 3, PRO PRICE 1, PRO PRICE 2, PRO PRICE 3, SOCIAL INFLU 1, SOCIAL INFLU 3, and BRAND IMG 3. including product features (PRO FEAT 1, PRO FEAT 2, PRO FEAT 3), PRO PRICE 1, PRO PRICE 2, PRO PRICE 3).

Table 10. Hypothesis Testing

HYPOTHESIS	VARIABLES (PATH)	P VALUE	STANDARDIZED REGRESSION WEIGHT	C.R	RESULT
H1	BI < PI	0.153	0.014	78.827	Good
H2	PP < PI	0.153	0.012	83.180	Good
H3	SI < PI	0.153	0.013	73.748	Good
H4	PF < PI	0.153	0.014	75.418	Good

D. Moderation Analysis

By introducing gender as a moderating factor, the research provides valuable insights for marketers targeting the dynamic preferences of users focused on DERs [26]. This gender-based moderation analysis will help understand how the influence of brand image, product features, price, user perceptions, and social impact on purchase intentions may vary between men and women consumers. The Findings from moderation effect are given in Table 11.

Table 11. Analysis of Moderation Effect

ANALYSIS OF PATHS	STANDARD DEVIATION (STDEV)	P VALUE	SAMPLE MEAN (M)
BI < PI	4.050	0.152	7.92
PP < PI	4.119	0.152	8.45
SI < PI	4.064	0.152	7.22
PF < PI	3.586	0.152	8.08

6. Conclusion

This study shows how important people's views towards brand value are when deciding to start using Distributed Energy Systems (DERs). According to our methods with Structured Equation Modeling (SEM), Data Analysis, Test of Validity, and Regression Analysis, we have also proven that a favorable outlook on products' value improves consumers' confidence and readiness to use such products. We have shown that robustness validates a measurement model through strict trials which is evidence for strong statistics in our findings and therefore strategic branding is vital in promoting sustainable energy solutions as shown by this study. Deriving from the high path coefficient and the significant explained variance, it is clear that brand value plays a critical role in the adoption of DERs. Therefore, it is essential for DER market companies to focus on the creation and preservation of a powerful brand image which will better nurture consumer trust and ease movement towards sustainable energy systems.

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