

Energy Cost Pressure and Financial Accessibility as Determinants of Solar PV Adoption among SMEs in Akinyele LGA, Oyo State, Nigeria.

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ABSTRACT

This study examined the economic and financial determinants of solar photovoltaic (PV) adoption among Small and Medium Enterprises (SMEs) in Akinyele Local Government Area of Oyo State, Nigeria. The study employed a quantitative, cross sectional survey design using structured questionnaires administered to 120 SME owners and managers. Principal Component Analysis (PCA) was used to identify the major economic and financial factors influencing solar PV adoption, and a binary logistic regression was used to test which of the extracted dimensions independently predict adoption. The results showed that the dataset was suitable for factor analysis, with a Kaiser Meyer Olkin (KMO) value of 0.752 and a significant Bartlett's Test of Sphericity ($p < 0.001$). The PCA extracted seven components explaining 73.31% of the total variance, namely Energy Cost Drivers, Financial Accessibility, Investment Capacity, Digital Payment Readiness, Affordability Constraints, Peer Influence, and Institutional Financial Support. The binary logistic regression model was statistically significant overall (chi square = 28.654, $p = 0.004$) and correctly classified 75.0% of cases, but only Investment Capacity independently predicted solar PV adoption ($\text{Exp}(B) = 2.576$, $p = 0.038$); the remaining six economic and financial dimensions, together with the demographic controls of gender, ownership type, and education, did not reach statistical significance. The findings indicate that although rising electricity tariffs, unstable grid pricing, and generator fuel costs remain prominent concerns for SMEs, it is firms' financial capacity and readiness to invest, rather than cost pressure or affordability perceptions alone, that most consistently distinguishes adopters from non-adopters. The study concludes that strengthening SMEs' investment capacity through targeted financing is central to accelerating solar PV adoption, and recommends flexible financing schemes, capacity-building support, and government incentive programs to enhance solar PV adoption among SMEs in Nigeria.

Index terms- Solar photovoltaic adoption; SMEs; Economic and financial determinants; Investment capacity; Financial accessibility; Akinyele LGA; Nigeria.

INTRODUCTION

Small and Medium Enterprises (SMEs) depend heavily on electricity for daily operations, yet unreliable power supply remains a major challenge in Nigeria. Frequent outages, rising electricity tariffs, and increasing generator fuel costs have significantly increased business operating expenses, especially for SMEs in semi-urban areas such as Akinyele LGA of Oyo State [1]. As a result, many firms are exploring alternative energy sources such as solar photovoltaic (PV) systems, which provide a cleaner and potentially more reliable source of power for businesses. However, despite Nigeria's high solar energy potential, adoption among SMEs remains relatively low. Economic and financial factors such as high installation costs, limited access to loans, and inadequate financial support may influence firms' decisions to adopt solar PV systems [2]. This study examines seven interrelated economic and financial dimensions of adoption, namely energy cost pressure, financial accessibility, investment capacity, affordability constraints, digital payment readiness, peer influence, and institutional financial support, to determine how energy cost pressure and financial accessibility, alongside these related dimensions, influence solar PV adoption among SMEs in Akinyele LGA, Oyo State, Nigeria.

Unreliable electricity supply and rising energy costs continue to affect the performance and sustainability of SMEs in Nigeria. Many SMEs rely on petrol and diesel generators, which increase operational costs due to rising fuel prices and maintenance expenses. Although solar PV systems offer an alternative source of electricity, adoption among SMEs remains low [3, 2]. High upfront installation costs, poor access to credit facilities, and limited financial support may discourage SMEs from adopting solar PV systems [4]. While previous studies [5] have examined renewable energy adoption in Nigeria, limited attention has been given to the economic and financial determinants of actual solar PV adoption among SMEs in Akinyele LGA of Oyo State. This study therefore examines the influence of energy cost pressure and financial accessibility, and the related economic and financial dimensions identified through Principal Component Analysis, on solar PV adoption among SMEs in Akinyele LGA, Oyo State, Nigeria.

Several empirical studies have applied multivariate statistical techniques such as Principal Component Analysis (PCA) to identify the underlying drivers of solar photovoltaic uptake and performance [6]. PCA is a dimensionality reduction technique that groups correlated variables into smaller components explaining the largest proportion of variance within a dataset [7], and it is particularly suited to studies involving multiple adoption indicators because it simplifies complex datasets into interpretable dimensions. Previous studies on renewable energy adoption have used PCA and related multivariate approaches to identify dimensions such as economic readiness, financial accessibility, social influence, and technological awareness [8]. Beyond Nigeria, household level evidence from Uganda shows that financial inclusion and access to credit significantly raise the likelihood of solar PV adoption and shape the type of system that is adopted [9, 10], while peer effects have been shown to meaningfully accelerate residential solar diffusion, as adoption by nearby households raises the visibility and perceived legitimacy of the technology [11]. At a macro level, the depth of domestic credit markets and the quality of financial institutions have also been linked to the pace of solar photovoltaic capacity expansion across emerging economies [12]. Taken together, this literature suggests that solar PV adoption is shaped jointly by cost pressures, financial access, investment readiness, and social and institutional dynamics, yet few studies have combined PCA-derived economic and financial dimensions with a regression-based test of which of these dimensions independently predict adoption among Nigerian SMEs. This gap motivates the present study, which examines how energy cost pressure and financial accessibility, alongside investment capacity, affordability constraints, digital payment readiness, peer influence, and institutional financial support, influence solar PV adoption among SMEs in Akinyele LGA, Oyo State, Nigeria.

METHODOLOGY

This section describes the research design, population and sampling procedure, data collection process, variable measurement, and analytical techniques used to examine the economic and financial determinants of solar PV adoption among SMEs in Akinyele LGA, Oyo State, Nigeria.

Research Design

The study adopted a quantitative, cross sectional survey design, appropriate for capturing the perceptions and adoption behaviour of small and medium enterprises at a single point in time. Principal Component Analysis (PCA) was used to reduce the correlated economic and financial variables into a smaller set of underlying dimensions, after which the resulting component scores were entered into a binary logistic regression model to test their association with solar PV adoption.

Study Population, Sample and Sampling Technique

The target population comprised registered and unregistered small and medium enterprises operating in Akinyele Local Government Area, Oyo State, Nigeria. A multi stage sampling technique was adopted to select a sample of 120 SME owners and managers, to whom a structured questionnaire was administered for data collection.

Data Collection

Primary data were collected using a structured questionnaire comprising sections on socio-economic attributes,

enterprise attributes, awareness of solar energy adoption, and economic and financial factors. The closed-ended items were measured on a five point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree).

Measurement of Variables

The dependent variable was solar PV adoption, measured as a binary variable based on whether a firm currently uses a solar energy system (Yes = 1, No = 0).

The independent variables comprised the seven economic and financial dimensions extracted through PCA:

- Energy Cost Drivers
- Financial Accessibility
- Investment Capacity
- Digital Payment Readiness
- Affordability Constraints
- Peer Influence
- Institutional Financial Support

Gender of the promoter, business ownership type, and educational level of the owner or manager were included as control variables in the regression model.

Method of Data Analysis

Data were analysed using both descriptive and inferential statistics. Descriptive statistics, including frequency distribution, percentage, mean, and standard deviation, were used to describe the characteristics of the sampled SMEs and respondents' perceptions and experience of solar energy adoption. Inferential statistics comprised Principal Component Analysis (PCA) and binary logistic regression. PCA was applied first to identify the underlying dimensions within the set of correlated economic and financial items, after which the resulting component scores were entered into the logistic regression model.

Principal Component Analysis

PCA was used to reduce dimensionality by transforming a set of possibly correlated observed variables into a smaller set of uncorrelated linear combinations, or principal components, while retaining as much of the variability in the original data set as possible. This technique was appropriate given the multidimensional nature of the economic and financial factors that could influence SMEs' adoption of solar energy, and the likely correlation among the measured variables. The use of component scores in the regression model further helps to avoid multicollinearity among the explanatory variables. Sampling adequacy was assessed prior to extraction using the Kaiser Meyer Olkin (KMO) measure and Bartlett's Test of Sphericity; a KMO value above 0.60 indicates good sampling adequacy, while a significant Bartlett's test ($p < 0.05$) confirms that the correlation matrix differs significantly from an identity matrix and is therefore suitable for component extraction. The k th principal component for p standardized observed variables is given as

$$PC_k = a_{k1}Z_1 + a_{k2}Z_2 + \dots + a_{kp}Z_p \quad (1)$$

where PC_k denotes the k th principal component, Z_j is the standardized value of the j th observed variable, and a_{kj} is the corresponding component coefficient. The coefficients were obtained from the eigenvectors of the correlation matrix R such that

$$R a_k = \lambda_k a_k \quad (2)$$

and the proportion of variance explained by each component is given as

$$VE_k = (\lambda_k / \Sigma \lambda) \times 100 \quad (3)$$

where k is the number of extracted components and $\Sigma \lambda$ is the sum of the eigenvalues of all extracted components.

Binary Logistic Regression

Since the dependent variable is binary, binary logistic regression was used to estimate the probability of solar PV adoption as a function of the principal component scores and the demographic control variables. The model is expressed as

$$P(Y = 1) = 1 / (1 + e^{-Z}) \quad (4)$$

where

$$Z = \beta_0 + \beta_1 PC_1 + \beta_2 PC_2 + \dots + \beta_k X_k \quad (5)$$

P is the probability of adopting solar energy, PC_i represents the principal component scores, X_i represents the additional control variables, and β_i denotes the regression coefficients.

RESULTS AND DISCUSSION

This section presents and discusses the findings on the economic and financial determinants of solar PV adoption among SMEs in Akinyele LGA, Oyo State, Nigeria. Descriptive statistics are first used to profile the sampled SMEs, after which Principal Component Analysis (PCA) and binary logistic regression are used to identify and test the economic and financial dimensions influencing adoption.

Demographic Characteristics of Respondents

Table 1 summarises the demographic characteristics of the respondents. The sample comprised 120 owners and managers, of whom 67 (55.8%) were female and 53 (44.2%) were male, indicating a slight predominance of female respondents. With respect to business ownership, the majority of enterprises were sole proprietorships, 113 (94.2%), while 7 (5.8%) operated as partnerships. Regarding education, 60 (50.0%) of the respondents had completed secondary education, 44 (36.7%) possessed tertiary education, 11 (9.2%) had primary education, and 5 (4.2%) had postgraduate qualifications. Concerning solar energy adoption, 42 respondents (35.0%) reported currently using solar energy, 66 (55.0%) indicated that they did not, and 12 (10.0%) did not respond to the question.

Table 1: Demographic Characteristics of the Respondents

Characteristic	Category	Frequency	Percentage
Gender	Female	67	55.8
	Male	53	44.2
Ownership type	Sole proprietorship	113	94.2
	Partnership	7	5.8
Education	Primary	11	9.2
	Secondary	60	50.0
	Tertiary	44	36.7
	Postgraduate	5	4.2

Current use of solar energy	Yes	42	35.0
	No	66	55.0
	No response	12	10.0

Source: Field Survey, 2026

(2) KMO and Bartlett's Test

Prior to conducting Principal Component Analysis, the suitability of the dataset was assessed using the Kaiser Meyer Olkin (KMO) measure of sampling adequacy and Bartlett's Test of Sphericity (Table 2). The KMO value of 0.752 exceeded the recommended minimum threshold of 0.70 [13], indicating adequate sampling adequacy. Bartlett's Test of Sphericity was also statistically significant (chi square (276) = 1757.058, $p < 0.001$), indicating that the correlation matrix was sufficiently correlated for factor extraction [14]. These results confirm that the economic and financial variables were appropriate for identifying the underlying determinants of solar PV adoption among SMEs.

Table 2: KMO and Bartlett's Test

Test	Value
KMO Measure of Sampling Adequacy	0.752
Bartlett's Test Approx. Chi-Square	1757.058
df	276
Sig.	< 0.001

Source: Field Survey, 2026

(3) Total Variance Explained

The PCA extracted seven components with eigenvalues greater than 1 (Table 3), which together explained 73.31% of the total variance, well above the commonly recommended 60% threshold for social science research and indicating satisfactory construct representation. Prior to rotation, the first component alone explained 29.42% of the total variance, while the remaining six components each contributed between 4.31% and 11.70%. Following Varimax rotation, the variance was more evenly distributed across the retained components, with the first rotated component explaining 16.65% of the variance and the remaining components contributing between 6.80% and 11.98%; this redistribution improved the interpretability of the extracted dimensions without altering the cumulative variance explained.

Table 3: Total Variance Explained (Initial Eigenvalues, Retained Components)

Component	Eigenvalue	% Variance	Cumulative %
1	7.060	29.417	29.417
2	2.809	11.703	41.120
3	2.152	8.965	50.085
4	1.966	8.192	58.278
5	1.368	5.699	63.977
6	1.206	5.026	69.003
7	1.034	4.307	73.310

Extraction Method: Principal Component Analysis. Source: Field Survey, 2026

(4) Economic and Financial Determinants of Solar PV Adoption among SMEs

The PCA identified seven distinct dimensions underlying SMEs' decisions to adopt solar energy systems (Table 4). The strongest construct was Energy Cost Drivers, characterised by rising electricity tariffs (loading = 0.853), inconsistent grid pricing (0.828), increasing generator fuel costs (0.804), and expected reductions in fuel expenditure (0.673). Financial Accessibility emerged as the second construct, reflecting the importance of flexible credit facilities (0.896), access to loans (0.862), and gradual payment options (0.681). Investment Capacity captured firms' financial strength and willingness to make long-term investments, with loadings ranging from 0.675 to 0.731. The remaining dimensions, Digital Payment Readiness, Affordability Constraints, Peer Influence, and Institutional Financial Support, each exhibited satisfactory factor loadings above the recommended threshold of 0.50.

Table 4: Rotated Factor Loadings of the Determinants of Solar PV Adoption among SMEs

Construct	Retained Variable	Factor Loading
Energy Cost Drivers	Rising electricity tariffs encourage our firm to seek alternative energy sources	0.853
	Inconsistent grid pricing makes solar energy more appealing	0.828
	Increasing generator fuel costs make solar energy more attractive	0.804
	Solar adoption is a way to reduce fuel expenditure	0.673
Financial Accessibility	Our firm would adopt solar energy if there were flexible credit options	0.896
	Access to loans or financing affects our ability to adopt solar energy	0.862
	Gradual payment options make solar energy systems more accessible	0.681
Investment Capacity	Even with high costs, our firm would consider investing in solar energy	0.731
	Our firm's financial strength determines our ability to afford solar systems	0.726
	We are willing to pay more initially for long-term energy savings	0.675
Digital Payment Readiness	We use mobile money or digital payments for energy-related transactions	0.904
	Mobile payment options make solar energy purchases more convenient	0.836
Affordability Constraints	The high upfront cost of solar energy discourages adoption	0.892
	Our firm considers solar energy too expensive to install initially	0.851
	Low-income firms face more difficulty adopting solar energy systems	0.522
Peer Influence	The affordability of solar energy is influenced by what similar firms can afford	0.843
	We often compare our energy investments with peer businesses	0.797

Institutional Support	Financial	Our firm has received information from banks about solar financing products	0.781
		Lending institutions support firms in financing renewable energy solutions	0.711

Extraction method: Principal Component Analysis; rotation method: Varimax with Kaiser normalization.
Source: Field Survey, 2026

Table 5 presents the reliability and descriptive statistics of the seven constructs extracted from the PCA. The retained constructs demonstrated satisfactory psychometric properties overall: factor loadings ranged from 0.522 to 0.904, indicating that all retained items exhibited acceptable associations with their respective constructs, and Cronbach's alpha coefficients ranged from 0.678 to 0.877, suggesting acceptable internal consistency for the measurement scales. Six of the seven constructs exceeded the conventional reliability threshold of 0.70, while Institutional Financial Support (alpha = 0.678) exhibited marginally lower reliability but remained acceptable for an exploratory two-item construct.

Table 5: Reliability and Descriptive Statistics of the Extracted Determinants of Solar PV Adoption

Construct	No. of Items	Loading Range	Cronbach's α	Mean	SD
Energy Cost Drivers	4	0.673 to 0.853	0.858	4.022	0.095
Financial Accessibility	3	0.681 to 0.896	0.862	3.644	0.187
Investment Capacity	3	0.675 to 0.731	0.795	3.756	0.045
Digital Payment Readiness	2	0.836 to 0.904	0.877	3.413	0.063
Affordability Constraints	3	0.522 to 0.892	0.728	3.597	0.277
Peer Influence	2	0.797 to 0.843	0.827	2.967	0.190
Institutional Financial Support	2	0.711 to 0.781	0.678	3.025	0.354

Source: Field Survey, 2026

Overall, the pattern of means indicates that Energy Cost Drivers (mean = 4.022) and Investment Capacity (mean = 3.756) were the dimensions most strongly endorsed by respondents, while Peer Influence recorded the lowest mean (2.967), suggesting that peer comparison plays a comparatively smaller role in shaping SMEs' stated attitudes toward solar PV adoption in the study area than cost pressure or firm-level financial readiness.

(5) Binary Logistic Regression Analysis

While Principal Component Analysis identifies the underlying dimensions among the correlated economic and financial variables, it does not by itself establish which of these dimensions significantly determine solar PV adoption. To address this, a binary logistic regression was estimated with solar PV adoption (1 = adopter, 0 = non-adopter) as the dependent variable, the seven PCA-derived component scores as predictors, and gender of the promoter, ownership type, and education level of the owner or manager included as control variables. The Omnibus test of model coefficients indicated that the overall model was statistically significant (chi square = 28.654, df = 12, p = 0.004), implying that the predictor variables jointly improved the prediction of solar PV adoption over the intercept-only model (Table 6).

Table 6: Omnibus Tests of Model Coefficients

	Chi-square	df	Sig.
Step	28.654	12	0.004
Block	28.654	12	0.004

Model	28.654	12	0.004
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The model summary (Table 7) showed Cox and Snell R-square and Nagelkerke R-square values of 0.233 and 0.316 respectively, indicating that the explanatory variables accounted for between 23.3% and 31.6% of the variation in solar PV adoption. The Hosmer and Lemeshow goodness-of-fit test was not statistically significant (chi square = 8.685, df = 8, p = 0.370), suggesting that the model adequately fitted the observed data (Table 8). The classification results (Table 9) showed that the model correctly classified 75.0% of the cases overall, with 84.8% of non-adopters and 59.5% of adopters correctly classified, demonstrating satisfactory predictive performance.

Table 7: Logistic Regression Model Summary

-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
115.688	0.233	0.316

Table 8: Hosmer and Lemeshow Test

Chi-square	df	Sig.
8.685	8	0.370

Table 9: Classification Table

Observed	Predicted: No	Predicted: Yes	% Correct
No	56	10	84.8
Yes	17	25	59.5
Overall Percentage			75.0

Dependent variable: Do you currently use solar energy? Source: Field Survey, 2026

The coefficient estimates (Table 10) revealed that Investment Capacity was the only variable that significantly influenced solar PV adoption among the sampled SMEs ($B = 0.946$, $p = 0.038$). The odds ratio ($\text{Exp}(B) = 2.576$) indicates that firms with greater investment capacity were approximately 2.6 times more likely to adopt solar energy systems than firms with lower investment capacity. Although gender of the promoter (female), ownership type (partnership), and education level of the owner or manager (postgraduate) exhibited relatively stronger effects, none reached statistical significance at the 5% level. Likewise, Digital Payment Readiness, Affordability Constraints, Peer Influence, Institutional Financial Support, Energy Cost Drivers, and Financial Accessibility did not significantly predict solar PV adoption. These findings suggest that while the explanatory variables jointly contributed to the prediction of solar PV adoption, investment capacity remained the only statistically significant independent determinant of adoption among the variables considered.

Table 10: Variables in the Logistic Regression Equation

Predictor	B	S.E.	Wald	df	Sig.	Exp(B)
Investment Capacity	0.946	0.457	4.295	1	0.038	2.576
Digital Payment Readiness	0.289	0.305	0.898	1	0.343	1.335
Affordability Constraints	-0.595	0.395	2.275	1	0.131	0.551
Peer Influence	0.006	0.266	0.001	1	0.981	1.006
Institutional Financial Support	-0.169	0.305	0.309	1	0.579	0.844
Energy Cost Drivers	0.214	0.337	0.401	1	0.526	1.238

Financial Accessibility	0.444	0.357	1.550	1	0.213	1.559
Gender of Promoter (Female)	0.855	0.493	3.007	1	0.083	2.351
Ownership Type (Partnership)	2.034	1.133	3.223	1	0.073	7.645
Education Level (Postgraduate)	-2.610	1.475	3.132	1	0.077	0.074
Constant	-5.193	2.188	5.632	1	0.018	0.006

Source: Field Survey, 2026

DISCUSSION OF FINDINGS

The findings of this study demonstrate that economic and financial factors play a central role in shaping SMEs' stated attitudes toward solar PV adoption in Akinyele LGA, Oyo State, but that only one of these factors, investment capacity, independently distinguishes actual adopters from non-adopters once all seven dimensions and the demographic controls are considered jointly. The PCA results revealed that the seven extracted components jointly explain 73.31% of the total variance in the underlying economic and financial items, confirming that financial considerations are a major organising theme in how SMEs think about renewable energy transition, even though the regression results show that this descriptive prominence does not automatically translate into independent predictive power for every dimension.

Energy Cost Drivers emerged as the strongest single dimension in the PCA, with high loadings for rising electricity tariffs (0.853), inconsistent grid pricing (0.828), and increasing generator fuel costs (0.804), and the highest mean score (4.022) among the seven constructs. This finding agrees with Akangbe and Sharifi [2], who found that reliability of power supply and total system cost were among the most significant determinants of solar PV adoption preferences among Nigerian SMEs, and with Akaeze and Akaeze [3], who documented the escalating production costs that generator-dependent SMEs face amid Nigeria's energy crisis. However, the logistic regression did not find Energy Cost Drivers to be a statistically significant independent predictor of adoption once the other components and controls were accounted for ($p = 0.526$). This apparent disagreement between the descriptive and regression results is not a contradiction; rather, it suggests that cost pressure is a near-universal concern that motivates SMEs to consider solar PV in principle, consistent with the wider literature, but that it does not by itself separate those who actually adopt from those who do not once firms' financial capacity is taken into account.

Financial Accessibility also loaded strongly, with flexible credit options (0.896) and access to loans (0.862) recording some of the highest loadings in the analysis. This is consistent with Aarakit et al. [10], who found that financial inclusion significantly increases the likelihood of household solar PV adoption in Uganda, and with Jiancheng et al. [12], who reported that domestic credit availability has a significant positive effect on solar photovoltaic capacity across emerging economies. However, Financial Accessibility was not a statistically significant independent predictor in this sample ($p = 0.213$), which diverges from the stronger, statistically confirmed role that financial inclusion plays in the Ugandan household studies [9, 10]. This divergence may reflect differences between SME and household decision-making, or the possibility that financial accessibility operates on adoption indirectly, by enabling the investment capacity that the regression does identify as significant, rather than as a direct, independent driver.

Investment Capacity was confirmed as the only statistically significant independent predictor of solar PV adoption ($\text{Exp}(B) = 2.576$, $p = 0.038$), with firms scoring higher on this dimension approximately 2.6 times more likely to adopt. This finding agrees with Akangbe and Sharifi [2], who reported that cost-saving expectations and long-term financial readiness were significant drivers of willingness to pay for solar PV among Nigerian businesses, and with the broader argument in Ogunyemi and Ishola [4] that data-driven financial solutions are central to unlocking renewable energy investment among SMEs. It is also consistent with household-level evidence from Uganda showing that financial capacity variables are among the strongest predictors of adoption once multiple factors are modelled jointly [9, 10]. This convergence across contexts strengthens the conclusion that it is firms' underlying financial strength and willingness to commit resources,

rather than cost pressure or affordability perceptions in isolation, that most reliably distinguishes adopters from non-adopters.

Affordability Constraints, capturing perceptions that solar systems are too expensive to install (0.892, 0.851), recorded a high descriptive mean (3.597) but was not a statistically significant independent predictor of adoption in the regression ($p = 0.131$), although the negative sign of the coefficient ($B = -0.595$) is in the expected direction. This result partially disagrees with Aarakit et al. [9], who found that affordability was the main driver of the type of solar PV system adopted in Uganda, and with the general expectation that upfront cost is decisive for resource-constrained firms. One plausible explanation is that, in this sample, affordability concerns are closely correlated with investment capacity, so that once investment capacity is included in the model, affordability constraints lose much of their independent explanatory power, a pattern of overlap that is common among correlated PCA-derived dimensions.

Digital Payment Readiness, reflecting the use of mobile money and digital payments for energy-related transactions (0.904, 0.836), was descriptively prominent (mean = 3.413, the highest reliability of all constructs at $\alpha = 0.877$) but was not a statistically significant independent predictor of adoption ($p = 0.343$). This finding only partly agrees with Aarakit et al. [10], who identified mobile money and remittance channels as key pathways through which financial inclusion drives solar PV adoption in East Africa; in the present sample, digital payment readiness appears to be a facilitating condition rather than an independent driver of the adoption decision itself.

Peer Influence, capturing the extent to which SMEs compare their energy investments and affordability with similar firms (0.843, 0.797), recorded the lowest mean of all seven constructs (2.967) and was not a statistically significant predictor of adoption ($p = 0.981$, the weakest association in the model). This finding disagrees with Bollinger and Gillingham [11], who found that adoption by nearby households significantly increased the probability of subsequent adoption in a large-scale study of residential solar diffusion. A likely explanation is that peer visibility and benchmarking, which are more easily observed among residential neighbours, may be weaker among SMEs in Akinyele LGA, where solar installations are less visible to competing businesses and where firms may be more reluctant to share cost information with peers.

Institutional Financial Support, reflecting information from banks about solar financing products and support from lending institutions (0.781, 0.711), showed the lowest reliability of the seven constructs ($\alpha = 0.678$) and was not a statistically significant predictor of adoption ($p = 0.579$). This result only partially agrees with Jiancheng et al. [12], who found that institutional quality jointly strengthens the deployment of solar photovoltaic capacity in emerging economies at a macro level; at the level of individual SMEs in this study, institutional support does not appear to translate into a measurable independent effect on the adoption decision, suggesting that awareness of financing products alone may be insufficient without accompanying investment capacity.

The demographic control variables provided additional context without altering the central finding. Gender of the promoter (female), ownership type (partnership), and education level of the owner or manager (postgraduate) all showed comparatively large coefficients, but none reached statistical significance at the 5% level ($p = 0.083$, 0.073 , and 0.077 respectively). These marginal associations suggest that firm structure and promoter characteristics may play a supporting role in adoption decisions and could reward further investigation with a larger sample, but they do not currently provide confirmed evidence of independent effects.

Overall, the PCA identified seven interpretable economic and financial dimensions underlying SMEs' solar PV adoption decisions in Akinyele LGA, but the binary logistic regression confirmed only Investment Capacity as a statistically significant independent predictor once the remaining dimensions and demographic controls were held constant. This pattern both agrees and disagrees with the wider literature in instructive ways: it agrees with studies that identify financial capacity and investment readiness as central to adoption [2, 9, 10], but it diverges from studies that find affordability constraints [9], digital financial inclusion [10], and peer effects [11] to be independently decisive, at least in the Nigerian SME context examined here. The findings therefore suggest that, while energy cost pressure and financial accessibility remain important in shaping how SMEs

perceive solar PV in principle, interventions aimed at strengthening firms' investment capacity, through savings mobilisation, asset-backed financing, or targeted grants, are likely to have the most direct and measurable effect on actual adoption.

CONCLUSION AND RECOMMENDATIONS

This study examined the economic and financial determinants of solar PV adoption among SMEs in Akinyele LGA, Oyo State, Nigeria, using Principal Component Analysis to identify seven underlying economic and financial dimensions, namely Energy Cost Drivers, Financial Accessibility, Investment Capacity, Digital Payment Readiness, Affordability Constraints, Peer Influence, and Institutional Financial Support, followed by a binary logistic regression to test which of these dimensions, together with selected demographic controls, independently predict adoption. The findings revealed that Investment Capacity was the only dimension that significantly predicted SME solar PV adoption ($\text{Exp}(B) = 2.576$, $p = 0.038$), with firms scoring higher on this dimension approximately 2.6 times more likely to adopt. Energy Cost Drivers, Financial Accessibility, Digital Payment Readiness, Affordability Constraints, Peer Influence, and Institutional Financial Support were prominent themes in the survey data and in the wider literature, but were not confirmed as statistically significant independent predictors in this sample. Gender of the promoter, ownership type, and education level of the owner or manager showed marginal but non-significant associations with adoption. Overall, the study concludes that solar PV adoption among SMEs in Akinyele LGA is shaped primarily by firms' financial capacity and readiness to invest, rather than by cost pressure, affordability perceptions, digital payment habits, peer comparison, or institutional support considered independently. Strengthening SMEs' investment capacity is therefore the intervention most directly supported by this study's evidence for increasing solar PV adoption among SMEs in Akinyele LGA and similar developing business environments.

Based on the findings of the study, the following recommendations are made:

1. Financial institutions should provide flexible loan schemes, asset-backed financing, and instalment payment options that specifically strengthen the investment capacity of SMEs, since this is the factor most directly associated with adoption.
2. Government and renewable energy agencies should introduce subsidy programs and incentives that reduce the effective cost of solar installation and free up capital for SME investment.
3. SME-focused renewable energy financing programs should be expanded to improve access to credit facilities, even though financial accessibility alone was not found to independently predict adoption in this study, as it remains an important enabling condition.
4. Solar energy providers should continue to promote digital and pay-as-you-go payment systems to improve affordability, while recognising that digital readiness alone may not be sufficient to drive adoption without accompanying investment capacity.
5. Awareness programs and peer-learning platforms should be strengthened to help SMEs share cost and performance information, given the comparatively limited role that peer influence currently plays in the study area.
6. Future research should replicate this analysis with a larger sample to test more robustly whether Energy Cost Drivers, Affordability Constraints, and Institutional Financial Support have independent effects that this study's sample size may not have had sufficient power to detect.

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