Jurnal Aplikasi Bisnis dan Manajemen (JABM), Vol. 12 No.3, September 2026
Permalink/DOI: http://dx.doi.org/10.17358/jabm.12.3.1080

Available online
http://journal.ipb.ac.id/index.php/jabm

WHO LEADS SUSTAINABILITY? IDENTIFYING CORPORATE CLUSTERS DRIVING THE LOW-CARBON TRANSITION

Widyaningsih Azizah[1], Herlan, Eka Sudarmaji

Faculty of Economics and Busines, Universitas Pancasila
Jl. Raya Lenteng Agung, Srengseng Sawah, Jagakarsa, South Jakarta City, Jakarta 12630, Indonesia

Article history:

Received
1 October 2025

Revised
25 February 2026

Accepted
11 August 2026

Available online
30 September 2026

This is an open access article under the CC BY license (https://creativecommons.org/licenses/by/4.0/)

Abstract:

Background: Climate change mitigation and the transition to sustainability require the accelerated adoption of energy efficiency (EE) technologies in the industrial and SME sectors. Although the economic and environmental benefits of these technologies are well documented, adoption rates remain far below their potential.
Purpose: This study investigates the financial, policy, and organisational determinants of energy efficiency (EE) technology adoption among industrial firms and SMEs in Greater Jakarta, where adoption rates remain significantly below their potential despite well-documented economic and environmental benefits. Drawing on Rogers' Diffusion of Innovations theory, the study examines how institutional support, managerial capability, access to financing, and technological readiness shape adoption outcomes in this context.
Design/methodology/approach: Using a 42-item Likert-type survey of 303 firms across Jakarta, Bekasi, and Tangerang, this study applied principal component analysis (PCA) to extract sustainability-oriented adoption factors, K-Means clustering to classify adopter types, and binary logistic regression to predict high-adoption status. Model diagnostics included reliability, ROC–AUC, Hosmer–Lemeshow, and multicollinearity checks.
Findings: Two groups were identified: Context-Advantaged firms, which leveraged networks and policy support, and Process-Strong firms, which demonstrated stronger internal capabilities and training. PCA identified 11 retained components, with policy clarity, managerial capability, and financing capacity emerging as key sustainability-related dimensions. The logistic regression model produced a ROC–AUC of 0.998 and a Nagelkerke R^2 of 0.964. Sectoral analysis indicated that manufacturing firms tended towards network- and policy-oriented pathways, whereas trade firms showed stronger process-oriented characteristics.
Conclusions: The findings indicate that EE technology adoption is associated with the convergence of internal capabilities, access to financing, and stable policy signals. The results support the integration of Diffusion of Innovations and Institutional Theory as a socio-technical framework for understanding corporate sustainability transitions. The study contributes an empirically grounded segmentation approach for EE policy design in emerging-market contexts.
Originality/value (State of the art): This study contributes by combining Diffusion of Innovations and Institutional Theory into a socio-technical framework that links the adoption of energy efficiency technologies to climate-mitigation goals. The results provide a practical segmentation of firms into Context-Advantaged and Process-Strong profiles and inform targeted policy approaches for accelerating the low-carbon transition among industrial firms and SMEs in Greater Jakarta.

Keywords: Sustainability, energy efficiency, corporate adoption, PCA, logistic regression

How to Cite:
Azizah, W., Herlan, & Sudarmaji, E. (2026). Who leads sustainability? Identifying corporate clusters driving the low-carbon transition. *Jurnal Aplikasi Bisnis dan Manajemen*, 12(3), 1080. https://doi.org/10.17358/jabm.12.3.1080

* Corresponding author:
Email: widyaningsih_azizah@univpancasila.ac.id

Copyright © 2026 The Author(s), ISSN: 2528-5149/EISSN: 2460-7819

INTRODUCTION

As the climate crisis worsens and energy consumption rises, there is an urgent need for a global transition to sustainable energy systems. Among the available strategies, energy efficiency (EE) technologies are widely recognised as crucial to achieving climate and sustainability goals. These technologies can significantly reduce greenhouse gas (GHG) emissions, enhance energy security, and generate cost savings (Nasip & Sudarmaji, 2023; Sudarmaji et al. 2021; Sudarmaji & Ambarwati, 2023; International Energy Agency [IEA], 2023). Despite these economic and sustainability benefits, adoption rates remain far below their potential, contributing to a persistent energy-efficiency gap (Ambarwati & Sudarmaji, 2023; Damayanti et al. 2024; Sudarmaji et al. 2024a; Saunders et al. 2021). Bridging this gap requires a deeper understanding of the socio-technical factors that facilitate or hinder adoption, particularly the characteristics that distinguish high-adopter firms from low-adopter firms in the industrial and SME sectors of Greater Jakarta.

According to Rogers' Diffusion of Innovations (DOI) theory, relative advantage, compatibility, complexity, trialability, and observability are five key characteristics that influence adoption decisions (Rogers, 2003). Recent empirical research suggests that, in EE contexts, technologies offering clear operational benefits, low perceived complexity, and strong compatibility with users' needs are more likely to be adopted (Zharova & Lee, 2022; Galster, 2025). However, adoption may remain constrained when technologies are perceived as risky or difficult to use, even when their sustainability benefits are apparent (Sudarmaji et al. 2024b).

Furthermore, adoption outcomes in the commercial and industrial sectors are significantly influenced by organisational context. Financial incentives, internal capabilities, and peer benchmarking can accelerate the adoption of EE measures (Nasip & Sudarmaji, 2018; Nasip & Sudarmaji, 2023; Sudarmaji et al. 2021; Bielig et al. 2024). Institutional Theory highlights the role of policies, subsidies, and standards in shaping adoption. Evidence from Swiss SMEs shows that targeted finance and knowledge-sharing networks can increase uptake (Fouiteh, 2024). Legitimacy Theory suggests that firms align their practices with values, norms, and regulations to maintain social legitimacy (Azizah & Wahyoeni, 2025; Fujianti et al. 2024; Azizah & Sudarmaji, 2026; Azizah et al. 2026). However, institutional channels can also amplify negative perceptions when early adopters experience technical problems, underscoring the importance of quality control (Shi et al. 2020).

This research employs a three-stage quantitative approach to identify and characterise high-adopter firms. First, PCA extracts sustainability-oriented adoption factors from the survey data. Second, K-Means clustering classifies firms into distinct adopter typologies based on these factors. Third, binary logistic regression predicts high-adoption status using institutional support, management expertise, financing availability, and technological readiness as predictors. The study aims to identify distinct groups of high-adopter companies with different strategic approaches to deploying energy efficiency technologies. It also develops a predictive model to differentiate firms with high and low adoption rates and examines sector-specific patterns, including process-oriented strategies among trade firms and network- and policy-oriented pathways among manufacturing firms. The study further examines whether stable policy frameworks, accessible green financing, and integrated management practices are associated with higher EE adoption.

Recent evidence reinforces DOI's view of EE diffusion. In China, perceived environmental benefits, cost savings, and lifestyle fit have been associated with EV uptake, whereas operational complexity can deter adoption (Xia et al. 2022). Cultural norms influence technology adoption in rural Italy (Baselice et al. 2021). Targeted incentives, peer success, and goal alignment can raise adoption (Gillingham & Palmer, 2014; Bielig et al. 2024). Institutional support, information networks, and policy incentives can accelerate SME uptake (Fouiteh, 2024), while multilayered policy mixes may outperform single policy instruments (Geels et al. 2017; Sovacool & Hess, 2017). Technological potential continues to grow, although infrastructure and complexity can limit diffusion (Ding, 2019; Huang, 2019). Behavioural variables should therefore be integrated into EE adoption models (Galster, 2025). Nevertheless, most studies examine elements of EE adoption independently including organisational readiness, institutional frameworks, behavioural drivers, and technological features, which limits understanding of how these factors interact during sustainability transitions. This study therefore employs a socio-technical systems perspective to investigate integrated adoption strategies that can address multiple barriers simultaneously.

METHODS

This study looked at survey responses from 303 corporate participants who represented industrial firms and SMEs in Jakarta, Bekasi, and Tangerang. A 42-item Likert-type questionnaire was used to document different facets of energy efficiency technology adoption behaviours. The survey items were grouped into predefined thematic construct blocks (A–G) that represented various aspects of the adoption process. Data cleaning involved median imputation for missing values to preserve distributional features after removing non-numeric entries and identifying information. All item responses were coded alphanumerically according to their construct block for consistency and ease of analysis (see Appendix A for methodological details). Median imputation was chosen to handle missing values in order to preserve the central tendency and form of Likert-type distributions (Little & Rubin, 2019). This method is commonly used in survey-based behavioural research, where listwise deletion may yield biased results. Each construct block's internal consistency was evaluated using Cronbach's alpha, and all scales had $\alpha > 0.7$.

This confirmed psychometric reliability in accordance with recognised sustainability adoption research protocols (Xia et al. 2022). Cronbach's alpha (α) was used to ensure that the items in each construct block consistently measured the intended latent variable. The $\alpha > 0.7$ cutoff point in sustainability adoption studies complies with psychometric guidelines (Nunnally & Bernstein, 1994; Xia et al. 2022). Principal Component Analysis (PCA) was used to reduce dimensionality while maintaining the basic variance structure of adoption behaviours. Components were retained based on scree plot analysis and cumulative explained variance, with an aim of approximately 80% of the total variance explained. Varimax rotation was applied to enhance interpretability. The adequacy of the sample was confirmed using the Bartlett's sphericity test ($p < 0.05$) and Kaiser-Meyer-Olkin (KMO > 0.7). The components that were kept were then used for clustering analysis.

The 42-item dataset was broken down into uncorrelated components using PCA to address Multicollinearity: Rotation, Varimax, to maximise interpretability; adequacy of sampling: KMO > 0.7 and Bartlett's test $p < 0.05$; retention criteria: scree plot inflexion points and ~80% cumulative explained variance. In line with previous EE research, this approach reduces complex socio-technical indicators to composite factors (Huang, 2019; Sovacool & Hess, 2017). Standardised principal component scores were subjected to K-Means clustering in order to identify natural groupings among participating firms. Different corporate adoption typologies were produced by evaluating cluster solutions for $k = 2$ to $k = 10$ using silhouette coefficient analysis in order to determine the optimal number of clusters. K-Means clustering on PCA scores ensured typologies were based on orthogonal factors to reduce redundancy (Hair et al. 2019). Weighing separation and cohesion allowed us to calculate the ideal k using silhouette coefficient analysis. A binary logistic regression model was developed to predict "High Adoption" outcomes, which are based on the median split of composite scores from the G-block (adoption outcomes and implementation success indicators). The retained principal components served as predictor variables along with covariates for technological readiness, regulatory support, and financial capability.

The model diagnostics included fit evaluation using the Hosmer–Lemeshow test and multicollinearity checks (variance inflation factors < 5). Discriminative ability was assessed using Receiver Operating Characteristic (ROC) analysis; an Area Under the Curve (AUC) > 0.75 was considered to have strong predictive performance. Binary logistic regression was used to model "High Adoption" (median split of G-block scores) as a function of contextual predictors (financial capability, regulatory support, and technological readiness) and retained principal components. ROC-AUC > 0.75 is a strong threshold for discrimination. Among the diagnostics were Fit: Hosmer–Lemeshow $p > 0.05$ desirable and Multicollinearity: VIF < 5. In terms of corporate EE adoption modelling, this framework follows empirical precedents (Gillingham & Palmer, 2014; Shi et al. 2020).

This study advances two main hypotheses. H1: Firms with stronger internal capabilities including managerial skills, training programs, and information systems, exhibit significantly higher rates of energy efficiency technology adoption. H2: Firms with greater access to institutional support such as clear policy signals, financing, and network participation show noticeably higher EE adoption than those with limited institutional access. The research framework is presented in Figure 1.

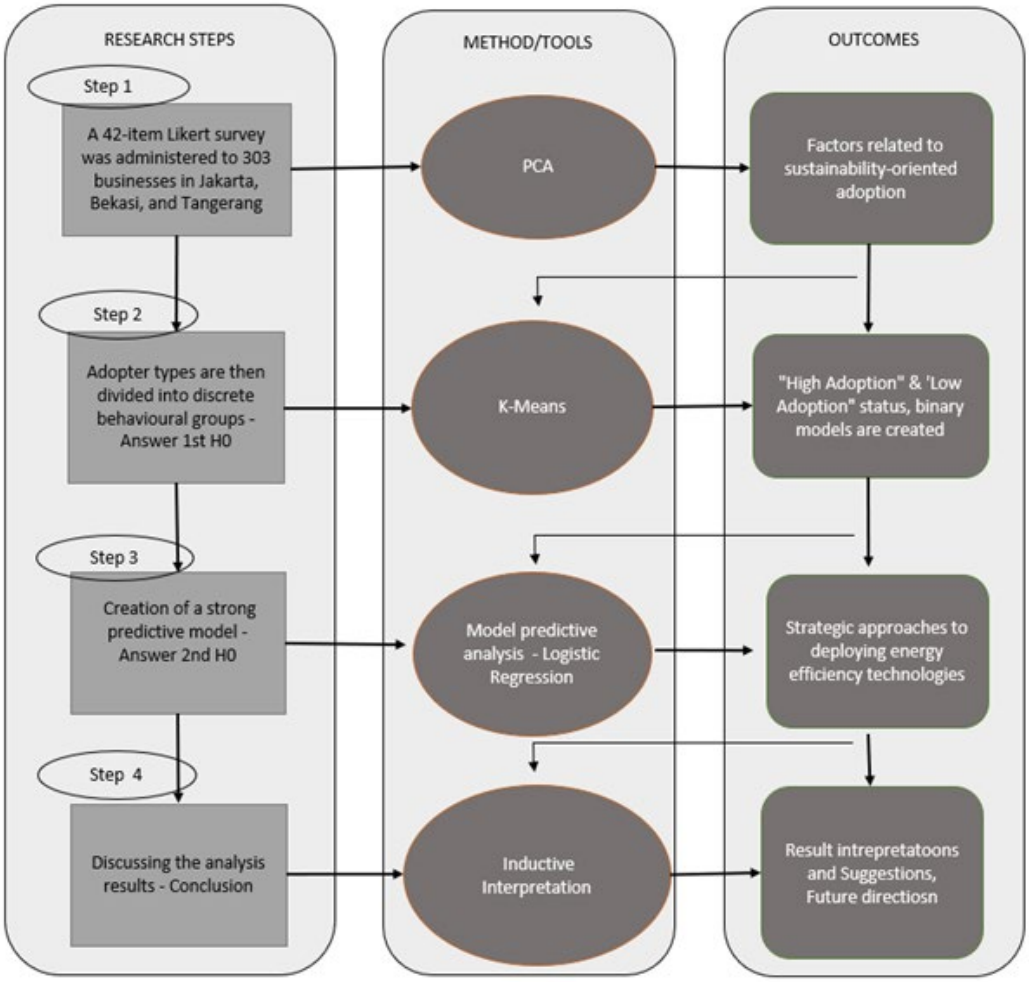


Figure 1. The research framework

RESULTS

Reliability and Validity

With Cronbach's α values ranging from 0.865 to 0.935 (Table 1), indicates strong reliability across blocks A–G, supporting predictive modelling. Consistency aligns with DOI determinants: relative advantage, compatibility, complexity, and institutional pressures: normative, coercive, mimetic, showing the instrument captures adoption drivers. Consistent organisational practices (energy management, structured audits) act as absorptive capacities translating policy signals into implementation (Schubert et al. 2021).

K-Means Clustering

K-Means clustering identified two groups among Jakarta firms (silhouette 0.346; Figure 2). The first cluster exhibits higher managerial engagement, training, and policy clarity reflecting stronger internal capacities and ties to institutional frameworks. The second shows lower readiness and tighter financing constraints.

This binary structure maps onto DOI stages: Cluster 1 resembles the early-majority, organisationally prepared to harness innovation benefits; Cluster 2 aligns with late adopters constrained by resources and legitimacy. Consistent with global evidence (Caporale et al. 2022; Dolšak et al. 2024), policy networks and alignment characterise Cluster 1, whereas Cluster 2 requires institutional interventions to overcome financing obstacles, especially liquidity. PCA Variance & Co-variance in Table 2.

Principal Component Analysis (PCA)

Approximately 80% of the variance was explained by the 11 components that PCA kept, the first few of which were energy-management ability, financing discipline, and policy understanding. Businesses that view technologies as compatible with their current capabilities and operational norms are better

positioned to adopt them, as the structure reflects DOI's compatibility and complexity dimensions. It also reflects the coercive aspect of institutional theory, which holds that adoption legitimacy is strengthened by fair and transparent policy rules that eliminate uncertainty. In line with DOI's emphasis on trialability and observability, two patterns are evident: first, information readiness and ease of use clustered with training and digital practices, and second, non-energy benefits productivity and quality gains likely support capability-oriented components. This is in line with research that links perceived co-benefits to higher adoption rates (Nehler & Rasmussen, 2016). With a distinct inflexion point at component 11, Figure 3, the Scree plot analysis offered more evidence in favour of keeping 11 components. According to this dimensional structure, eleven fundamental underlying factors can be used to understand corporate energy efficiency adoption. Each of these factors represents a different aspect of the adoption process.

Logistic Regression and ROC Analysis

To categorise corporations into high and low adoption groups, the predictive modelling phase employed a logistic regression framework with the 11 retained principal components as predictor variables. Logistic Regression Decision (PCA 1 vs PCA 2) in Figure 4.

Table 1. Reliability

Construct	NumItems	CronbachAlpha
A	6	0.882
B	6	0.865
C	6	0.935
D	6	0.890
E	6	0.929
F	6	0.921
G	6	0.915

Table 2. PCA Variance & Co-variance

PC	Explained Variance Ratio	Cumulative Variance
1	0.5732	0.5732
2	0.0467	0.6199
3	0.0272	0.6471
4	0.0252	0.6723
5	0.0224	0.6947
6	0.0211	0.7158
7	0.0194	0.7353
8	0.0178	0.7531
9	0.0169	0.7700
10	0.0154	0.7854
11	0.0146	0.8000
12	0.0134	0.8135
13	0.0123	0.8259
14	0.0115	0.8374
15	0.0109	0.8483

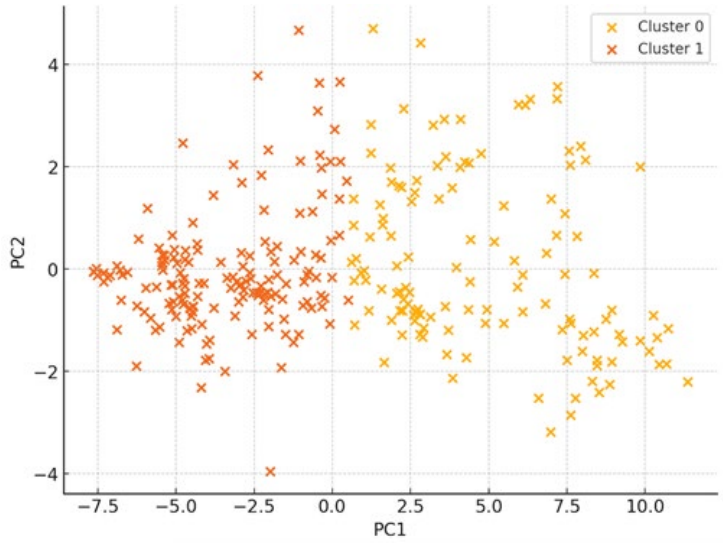


Figure 2. PCA Plot with K-Mean Cluster (K=2)

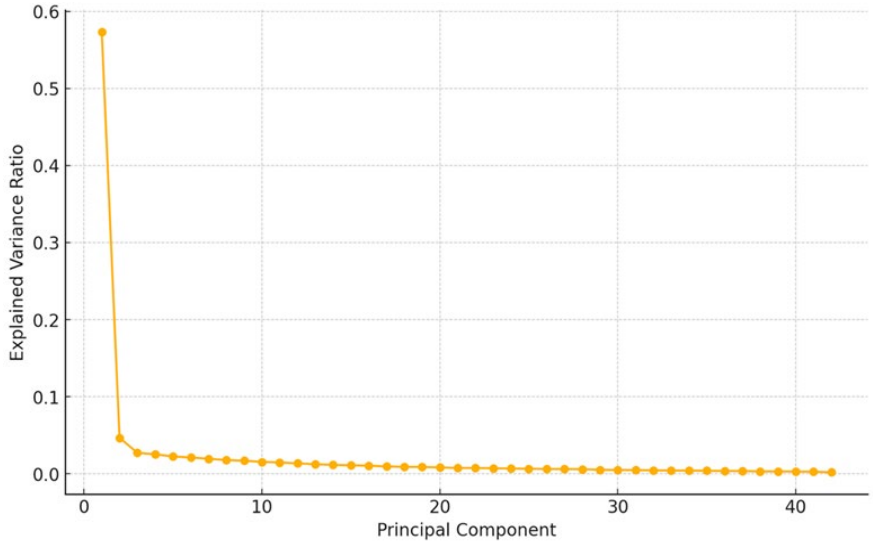


Figure 3. Scree Plot

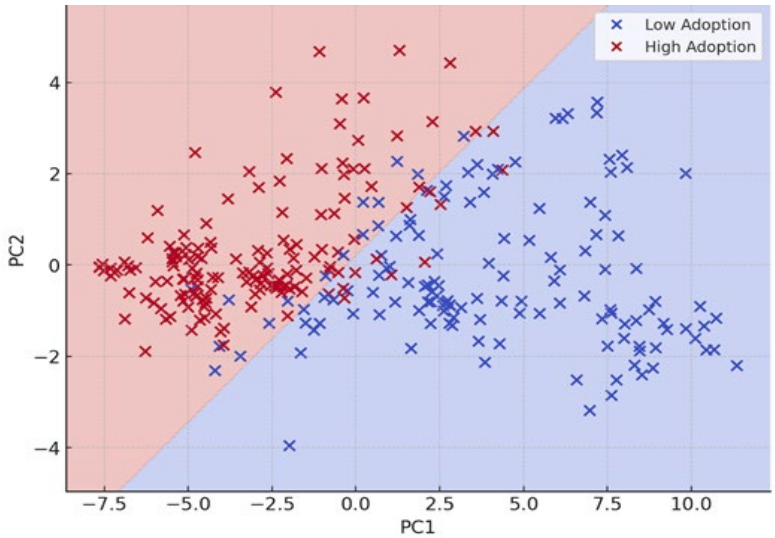


Figure 4. Logistic Regression Decision (PCA 1 vs PCA 2)

With a ROC analysis Area Under the Curve of 0.998 (Figure 5), the logistic regression model showed remarkable predictive performance. Among corporations in the Jakarta area, this exceptionally high AUC value demonstrated nearly perfect discriminative ability in differentiating between high and low adoption outcomes. A near-perfect ability to discriminate between high and low adopters across all potential classification thresholds was demonstrated by the Receiver Operating Characteristic analysis, which produced an Area Under the Curve of 0.998. This remarkable AUC value demonstrated the model's nearly perfect ability to rank-order cases based on their likelihood of adoption, which makes it incredibly useful for real-world uses like determining which companies stand to gain the most from focused energy efficiency initiatives. With an AUC of 0.998, logistic regression employing the top 8 principal components demonstrated remarkable differentiation between firms with high and low adoption rates. The model's high explanatory power (Nagelkerke R2 = 0.964) highlights its capacity to account for the contextual and organisational factors that influence adoption. Components related to energy-management and financing capacity were significant positive predictors, these were crucial in both the resource dependency perspective of Institutional Theory and the relative advantage dimension of DOI.

The classification performance metrics further validated the model's strong predictive abilities. A balanced performance was achieved, avoiding high overall accuracy at the expense of subpar performance on minority classes, as indicated by precision and recall values that both exceeded 0.70 across classification categories. Using a standard 0.50 probability threshold for classification decisions, the overall accuracy was 97.4% across the entire dataset (Table 3). With an actual positive rate of 97.6% and a true negative rate of 97.1%, the model demonstrated an impressive balance between sensitivity and specificity. By correctly identifying both high-adoption and low-adoption cases, the model avoided the common issue of achieving high overall accuracy through biased prediction towards the majority class, as evidenced by its balanced performance. The confusion matrix provided transparency into the precise types of prediction errors the model made by offering a thorough breakdown of correct and incorrect classifications at the 0.50 threshold. The model's significant discriminative value was confirmed by the ROC curve's position well above the diagonal chance line, which illustrated the model's performance across the entire range of classification thresholds.

To guarantee the validity of model inferences, critical statistical assumptions underlying logistic regression were methodically assessed. Variance Inflation Factors for all retained principal components ranged from 1.00 to 1.00, according to the multicollinearity assessment, which is significantly lower than the typical threshold of 5.0 that would suggest problematic multicollinearity. The correlations between each continuous predictor and the logit transformation of the model were examined in order to assess the linearity of the logit assumption. There was no indication of significant nonlinearity that would go against the core tenets of logistic regression, and these correlations ranged from -0.88 to 0.31 (Table 4).

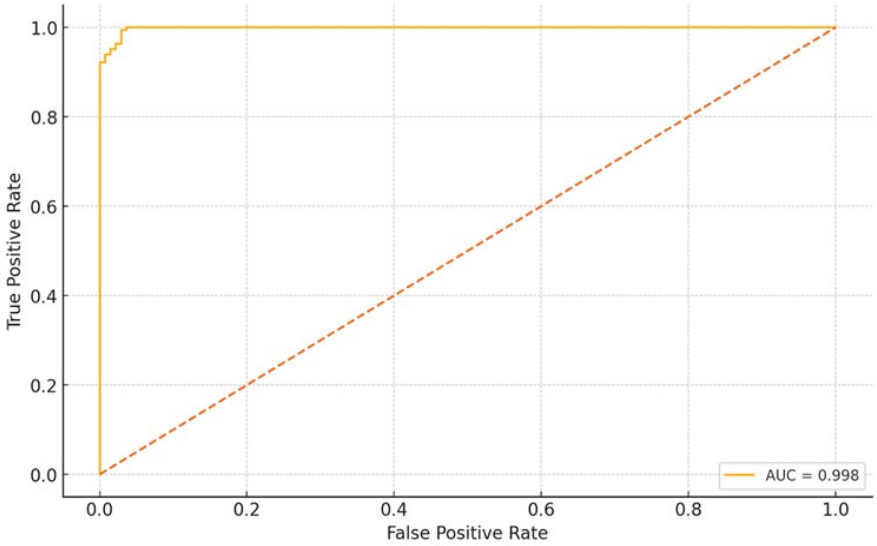


Figure 5. ROC Curve

The Hosmer-Lemeshow goodness-of-fit test (Table 5) was used to evaluate model calibration. The results yielded a chi-square statistic of 0.494 with 8 degrees of freedom and a p-value of 1.000. The non-significant chi-square (p = 1.000) confirms that the model's predicted probabilities closely matched the observed outcomes across all risk deciles — indicating adequate calibration, with no systematic over-prediction or under-prediction of adoption across the spectrum of predicted risk. The model distinguishes between firms with high and low adoption rates with significant accuracy by using the Enter method, which introduces all retained PCs at once (refer to the confusion matrix and ROC figure).

VIFs are comfortably below standard thresholds, reflecting the orthogonality of PCA inputs; correlations with the logit did not reveal significant linearity violations; and the Hosmer–Lemeshow statistic indicates adequate calibration across predicted-risk deciles. A one-unit increase in those latent scores increases the likelihood of high adoption. PCs linked to financing and energy-management capabilities generally have positive, statistically significant coefficients and odds ratios > 1. This is in line with studies that demonstrate how financing support and policy tools (such as white certificates and obligation schemes) crowd in EE investments and even improve firm performance, as well as quasi-experimental and econometric evidence that links audits and structured management practices to actual implementation (Schubert et al. 2021; Caragliu, 2021). Robustness (multicollinearity, linearity, and calibration) was validated by statistical assumption checks.

Strategic Differentiation Among High Technology Adopters

PCA visualisation confirms clear separation among top adopters **(**Figure 6). Sectoral patterns reveal that Cluster A (38 firms), dominated by trade, reflects a structured, process-optimising adoption; Cluster B (18 firms) is heavier in manufacturing, indicating innovation- and network-based pathways. Services Firms are evenly distributed (22/22), while Others Firms tilt to Cluster B (11/21), underscoring the role of policy support and networks. The distribution by business field is summarised in Table 6. These findings align with evidence that sector-specific operations shape mechanisms and pathways of technology adoption (Sardianou & Genoudi, 2013).

Table 3. The confusion matrix

	Pred Low Adoption	Pred High Adoption
Actual Low Adoption	134	4
Actual High Adoption	4	161

Table 4. VIF and regression coefficients, significance, and odds ratios

Variable	B	SE	z	p_value	Exp(B)	VIF	Corr_with_Logit
Intercept	0.2117	0.648	0.3266	0.7440	1.2357		
PC1	-3.4891	0.9335	-3.7378	0.0002	0.0305	1.000	-0.880
PC2	4.2757	1.1901	3.5926	0.0003	71.9272	1.000	0.306
PC3	3.5590	1.0975	3.243	0.0012	35.1298	1.000	0.196
PC4	-1.2364	0.6801	-1.8181	0.0690	0.2904	1.000	-0.063
PC5	-2.7798	0.8031	-3.4613	0.0005	0.0621	1.000	-0.138
PC6	-2.7325	0.8677	-3.1491	0.0016	0.0651	1.000	-0.136
PC7	2.3094	0.9024	2.5592	0.0105	10.0688	1.000	0.106
PC8	4.6409	1.7171	2.7028	0.0069	103.6365	1.000	0.203

Restricting analysis to high adopters yields two strategic profiles. Based on Table 6**,** Cluster A, trade-sector firms with higher capability/training, pursue resource-intensive, structured routes prioritising capacity building and procedural integration; services within this cluster likely emphasise methodical operational enhancements. The smaller manufacturing presence (10 firms) suggests different industrial approaches. Cluster B**,** manufacturing-leaning exhibits higher policy (network) scores and relies on external institutional links and innovation ecosystems, Others firms (21) and Services Firms (22) here indicate that network-oriented, policy-leveraged adoption spans diverse industries, while trade (23) is relatively less represented, favouring flexible, market-responsive strategies. These trends illustrate that even among high adopters, sectoral context shapes strategic orientation: manufacturing/diverse industries gravitate to innovation/network pathways; trade dominates process-focused adoption

Organisations that adopt primarily because of internal fit and relative advantage are represented by Cluster A from a DOI perspective. In contrast, adoption motivated by network effects and external legitimacy is represented by Cluster B. According to institutional theory, Cluster B gains from more powerful normative and coercive forces, like professional networks and regulatory alignment. Targeting adoption interventions is directly affected by these differences: for Process-Strong firms, prioritise skill development, operational integration, and ROI metrics; for Context-Advantaged firms, prioritise policy incentives, cooperative opportunities, and ecosystem engagement.

Globally, there is an urgent need to transition to sustainable energy systems due to the escalating climate crisis and increasing energy consumption. To close this gap, a deeper understanding of the socio-technical factors that facilitate or hinder uptake is required, especially an understanding of the characteristics that set high-adopter firms apart from low-adopter firms in the industrial and SME sectors of Greater Jakarta when it comes to the implementation of energy efficiency technologies.

Table 5. Hosmer-Lemeshow goodness-of-fit test

n	obs_1	exp_1	obs_0	exp_0
31	0	0	31	31
30	0	0	30	30
30	0	0.001	30	29.999
30	0	0.118	30	29.882
31	14	14.243	17	16.757
30	30	29.64	0	0.36
30	30	29.997	0	0.003
30	30	30	0	0
30	30	30	0	0
31	31	31	0	0

Table 6. High adopters cluster

The Business Field of the Company	Cluster-0 (Cluster A)	Cluster-1 (Cluster B)
Services Firm	22	22
Others Firm	11	21
Manufacturing Firm	10	18
Trade Firm	38	23

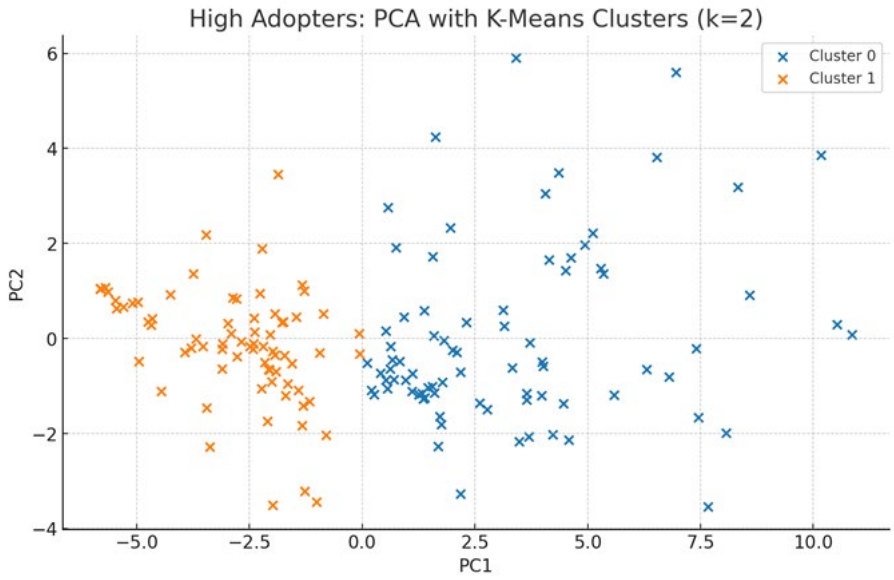


Figure 6. High Adopters: PCA with K-Means Cluster

Rogers' DOI emphasises relative advantage, compatibility, trialability, complexity, and observability (Rogers, 2003). Empirical work shows operational benefits, low complexity, and user compatibility lift uptake (Zharova & Lee, 2022; Galster, 2025), while perceived risk hinders it. Organisational levers, peer benchmarking, internal capacity, and incentives, accelerate adoption (Nasip & Sudarmaji, 2018; Nasip & Sudarmaji, 2023; Sudarmaji et al. 2021; Bielig et al. 2024), and aligning sustainability plans with EE builds commitment (Fouiteh, 2024). Institutionally, policy frameworks, subsidies, and standards matter targeted finance and knowledge networks raise SME uptake, but early failures can spread negative perceptions, hence quality control (Fouiteh, 2024; Shi et al. 2020). Behavioural factors also contribute technology, combined with behaviour change, increases savings (Dietz et al. 2009); perceived environmental impact, values, and norm compliance shape willingness (Schulte et al. 2021).

The findings provide strong support for the first hypothesis, which holds that companies with more robust internal capabilities have higher adoption rates. With odds ratios above 1.0 and statistical significance levels below 0.05, the logistic regression analysis revealed that the principal components associated with financing discipline and energy management ability emerged as significant positive predictors of high adoption status. Additionally, the K-Means clustering analysis showed a clear "Process-Strong" cluster, primarily composed of trade-sector companies with high capability and training scores. This suggests a methodical, process-oriented adoption pathway that leverages internal organisational strengths.

The evidence is equally firm regarding the second hypothesis, which concerns the influence of institutional support on adoption rates. Policy clarity was identified as one of the primary sustainability drivers by the PCA analysis, which also explained a significant portion of the variation in adoption patterns. Higher policy support and network scores were displayed by businesses in the "Context-Advantaged" cluster, indicating tactics that effectively utilise outside institutional frameworks and innovation ecosystems. Furthermore, the sectoral analysis revealed that manufacturing firms tended to follow policy-driven and network-based pathways. In contrast, firms from various sectors that utilised institutional support systems exhibited adoption patterns that differed significantly from those of firms with limited access.

These trends support a multi-theoretical interpretation in which Institutional Theory explains how a combination of normative pressures from training programs and managerial norms, coercive pressures from policy frameworks, and mimetic pressures from peer learning networks shapes adoption pathways. Concurrently, firms' perceived advantages, compatibility evaluations, and benefit observability impact their readiness for adoption, as explained by the Diffusion of Innovations theory. When internal capabilities and external institutional support are in synergy, positive feedback loops of legitimacy and organisational readiness are created, significantly increasing the likelihood

of achieving high adoption status, according to the integration of these theoretical perspectives. With a ROC-AUC of 0.998 and the capacity to account for 96.4% of the variance in high-adoption likelihood, the model's remarkable predictive performance makes this finding especially clear. It shows that institutional support and internal capabilities work together to create a potent predictor of the success of energy efficiency technology adoption.

Managerial Implications

For managers, the findings suggest institutionalising training, standard operating procedures, and digital measurement and verification within energy-management systems so that perceived advantages, compatibility, and observability can be translated into day-to-day practice. Managers should also strengthen internal capabilities, particularly employee training, energy-management practices, information systems, and monitoring mechanisms, to improve the organisation's readiness to adopt energy-efficiency technologies. In addition, managers should integrate energy-efficiency investments into operational planning and evaluate their financial and non-financial benefits as part of the firm's long-term competitiveness strategy. Policymakers, lenders, and industry associations may consider clearer technical roadmaps, accessible green-finance mechanisms, and stronger peer networks to reduce uncertainty and facilitate knowledge exchange.

CONCLUSIONS AND RECOMMENDATIONS

Conclusions

The results of our cross-sectional analysis demonstrate a consistent and repeatable adoption pattern: when three factors are combined, companies are more likely to adopt energy-efficiency measures: (i) strong internal capabilities, such as targeted training, robust information flows, and continuous monitoring; (ii) credible access to financing, whether through external loans, implementation support programs, or internal budgeting discipline; and (iii) stable, clear policy signals that reduce uncertainty and direct investment. It is worth noting that the ROC–AUC of 0.998 exceeds typical thresholds in comparable EE adoption studies, which generally range from 0.70 to 0.90. This result likely reflects the orthogonality of PCA-derived predictors which, by construction, eliminate multicollinearity combined with the homogeneity of the Greater Jakarta sample. Caution is therefore warranted in generalising these findings to more heterogeneous populations or different institutional contexts. This trio supports important findings from recent empirical research, which demonstrates that regulatory tools crowd in private investment (Caragliu, 2021), audits and energy-management systems consistently drive uptake (Schubert et al. 2021), and financial barriers persist, especially for SMEs (Caporale et al. 2022). Accessible financing, linked to verified savings and structured management interventions (audits, benchmarking, EMS), is strategically combined in an effective policy portfolio to accelerate adoption, which is backed by transparent and predictable regulatory frameworks. This approach aligns corporate incentives with long-term competitiveness and decarbonisation goals by tackling the behavioural and structural frictions associated with the "efficiency gap."

Recommendations

The study suggests to the adoption literature by integrating diffusion-of-innovation (DOI) and institutional theory into a cohesive, empirically grounded framework. The clustering and PCA results from a DOI perspective highlight perceived compatibility, trialability, and relative advantage, which are translated into concrete managerial skills and access to resources. Network participation and policy clarity are normative and regulatory factors that impact adoption behaviour, especially for companies that operate in cooperative or compliance-driven environments, according to an institutional theory perspective. Principal component-based predictive modelling, unsupervised clustering, and construct-level reliability checks are all combined in the methodological design to create a reproducible template for identifying high-probability adopters in diverse policy contexts. In reality, the sectoral differentiation among high adopters provides policymakers and technology providers with actionable insights: innovation and network-based approaches are more beneficial for manufacturing and diversified industries. At the same time, process-oriented interventions have a substantial effect on trade-sector businesses. This fine-grained knowledge can guide monitoring, incentive design, and targeted outreach strategies that maximise program impact.

Several limitations constrain the scope of the findings. First, because the data are cross-sectional, causal inference is limited; the interpretations are based on observed associations rather than established causal relationships. Second, the principal components combine multiple managerial practices, which may stabilise the model and reduce multicollinearity but can obscure which specific practices are most influential. Future studies could link survey responses to administrative programme data or use panel designs to estimate the effects of audits, financing programmes, or regulatory interventions. Third, defining "high adoption" using the median of the G-block score simplifies a continuous adoption spectrum. Future research could test alternative thresholds or alternative outcome specifications, including models tailored to different types of energy-efficiency measures. Finally, researchers should carefully consider the number of retained components relative to sample size and should report sensitivity analyses using alternative component-retention criteria. Addressing these issues would strengthen the theoretical and practical applicability of the findings.

REFERENCES

Ambarwati, S., & Sudarmaji, E. (2023). Determinant factors of energy consumption savings in urban households. *Jurnal Aplikasi Bisnis dan Manajemen*, 9(2), 440–454.

Azizah, W., & Sudarmaji, E. (2026). Sustainability accounting compliance under IFRS S2: Carbon emission disclosure in public enterprises across three regulatory phases, a systematic literature review. *Journal of International Accounting, Taxation and Information Systems*, 3(2), 58–68.

Azizah, W., & Wahyoeni, S. I. (2025). Bridging the gap: Assessing Indonesian companies' compliance with national regulatory standards and IIRF in the context of SDGs. *Journal of Lifestyle and SDG'S Review,* 5(1), 1–28.

Azizah, W., Sudarmaji, E., & Fredy, H. (2026). Sustainability accounting compliance under IFRS S2: Carbon emission disclosure in Indonesian state-owned enterprises across three regulatory phases. *International Journal of Accounting and Economics Studies*, 13(1), 393–400.

Baselice, A., Lombardi, M., Prosperi, M., Stasi, A., & Lopolito, A. (2021). Key drivers of the engagement of farmers in social innovation for marginalised rural areas. *Sustainability,* 13(15), 8454. https://doi.org/10.3390/su13158454

Bielig, M., Kacperski, C., & Kutzner, F. (2024). Increasing retrofit device adoption in social housing: Evidence from two field experiments in Belgium. *Energy Policy,* 182, Article 113794.

Caporale, G. M., Gil-Alana, L. A., Plastun, A., & Makarenko, I. (2022). Small and medium-sized European firms and energy efficiency investment: The role of financing and audits (CESifo Working Paper No. 10066). Center for Economic Studies and ifo Institute (CESifo). https://www.ifo.de/DocDL/cesifo1_wp10066.pdf

Caragliu, A. (2021). Energy efficiency-enhancing policies and firm performance: Evidence from the paper and glass industries in Italy. *Energy Policy*, 156, Article 112415. https://doi.org/10.1016/j.enpol.2021.112415

Damayanti, S., Sudarmaji, E., & Masrio, H. (2024). The critical role of energy intensity in decarbonizing ASEAN: Integrating growth and emissions reductions. *International Journal of Energy Economics and Policy*, 14(3), 247–259.

Dietz, T., Gardner, G. T., Gilligan, J., Stern, P. C., & Vandenbergh, M. P. (2009). Household actions can provide a behavioral wedge to rapidly reduce US carbon emissions. *Proceedings of the National Academy of Sciences,* 106(44), 18452–18456. https://doi.org/10.1073/pnas.0908738106

Ding, Y. (2019). Automotive Li-Ion batteries: Current status and future perspectives. *Electrochemical Energy Reviews,* 2(2), 199–223. https://doi.org/10.1007/s41918-019-00028-3

Dolšak, J., Hrovatin, N., & Zorić, J. (2024). What impacts the strength of perceived barriers to and drivers of energy efficiency in manufacturing SMEs? *Heliyon,* 10(1), Article e24020. https://doi.org/10.1016/j.heliyon.2024.e24020

Fouiteh, I. (2024). Unraveling the adoption patterns of energy efficiency measures in Swiss SMEs. *Journal of Cleaner Production,* 433, Article 139897.

Fujianti, L., & Team. (2024). Good corporate governance dan environmental, social, governance disclosures di Indonesia. *Jurnal Reviu Akuntansi dan Keuangan*, 14(1), 19–36.

Fujianti, L., Azizah, W., & Rizal, N. (2024). The double-edged sword of transparency: ESG disclosure's effect on competitive dynamics in manufacturing. *Jurnal Reviu Akuntansi dan*

Keuangan, 8(6), 1735–1750.

Galster, H. S. (2025). Integrating behavioral drivers into energy efficiency modeling: A systematic review. *Renewable and Sustainable Energy Reviews,* 189, Article 113977. https://doi.org/10.1016/j.rser.2024.113977

Geels, F. W., Sovacool, B. K., Schwanen, T., & Sorrell, S. (2017). Sociotechnical transitions for deep decarbonization. *Science,* 357(6357), 1242–1244. https://doi.org/10.1126/science.aao3760

Gillingham, K., & Palmer, K. (2014). Bridging the energy efficiency gap: Policy insights from economic theory and empirical evidence. *Review of Environmental Economics and Policy,* 8(1), 18–38. https://doi.org/10.1093/reep/ret021

Hair, J. F., Black, W. C., Babin, B. J., & Anderson, R. E. (2019). Multivariate data analysis (8th ed.). Cengage Learning.

Huang, C., Zappone, A., Alexandropoulos, G. C., Yuen, C., & Debbah, M. (2019). Reconfigurable intelligent surfaces for energy efficiency in wireless communication. *IEEE Transactions on Wireless Communications,* 18(8), 4157–4170. https://doi.org/10.1109/TWC.2019.2922609

International Energy Agency. (2023). Energy efficiency 2023: Analysis and outlooks to 2030. IEA. https://www.iea.org/reports/energy-efficiency-2023

Little, R. J. A., & Rubin, D. B. (2019). Statistical analysis with missing data (3rd ed.). John Wiley & Sons.

Nasip, I., & Sudarmaji, E. (2018). Government measures to promote new retrofitting business and financing option in Indonesia. *International Journal of Engineering and Technology*, 7(3.25), 25–28.

Nasip, I., & Sudarmaji, E. (2023). Energy efficient retrofits using transaction cost theory: Evidence from Indonesia. *Jurnal Ekonomi Malaysia,* 57(3), 1–15.

Nehler, T., & Rasmussen, J. (2016). How do firms consider non-energy benefits? Empirical findings on energy-efficiency investments in Swedish industry. *Journal of Cleaner Production,* 113, 472–482. https://doi.org/10.1016/j.jclepro.2015.11.070

Nunnally, J. C., & Bernstein, I. H. (1994). *Psychometric* theory (3rd ed.). McGraw-Hill.

Rogers, E. M. (2003). *Diffusion of innovations* (5th ed.). Free Press.

Sardianou, E., & Genoudi, P. (2013). Which factors affect the willingness of consumers to adopt renewable energies? *Renewable Energy*, 57, 1–4. https://doi.org/10.1016/j.renene.2013.01.031

Saunders, H. D., Roy, J., Azevedo, I. M. L., Chakravarty, D., Dasgupta, S., De La Rue Du Can, S., Druckman, A., Fouquet, R., Grubb, M., Lin, B., Lowe, R., Madlener, R., McCoy, D. M., Mundaca, L., Oreszczyn, T., Sorrell, S., Stern, D., Tanaka, K., & Wei, T. (2021). Energy efficiency: What has research delivered in the last 40 years? *Annual Review of Environment and Resources*, 46, 135–165.

Schubert, T., Breitschopf, B., & Plötz, P. (2021). Energy efficiency and the direct and indirect effects of energy audits and implementation support programmes in Germany. *Energy Policy,* 157, Article 112486.

Schulte, E., Scheller, F., Sloot, D., & Bruckner, T. (2021). A meta-analysis of residential PV adoption: The role of perceived benefits and antecedents in solar energy acceptance. *Renewable Energy*, 179, 1294–1306.

Shi, Y., Zeng, Y., Engo, J., Han, B., Li, Y., & Muehleisen, R. T. (2020). Leveraging inter-firm influence in the diffusion of energy efficiency technologies: An agent-based model (arXiv:2004.11536). arXiv. https://arxiv.org/abs/2004.11536

Sovacool, B. K., & Hess, D. J. (2017). Ordering theories: Typologies and conceptual frameworks for sociotechnical change. *Social Studies of Science,* 47(5), 703–750. https://doi.org/10.1177/0306312717709363

Sudarmaji, E., & Ambarwati, S. (2023). Do nudges and prepaid electricity token lead to electricity savings? Analysis of urban consumption behaviour in Indonesia. Atlantis Press International BV.

Sudarmaji, E., Achsani, N. A., Arkeman, Y., & Fahmi, I. (2021). Alternative PSS business models of ESCO: Towards an innovative new model. *Indonesian Journal of Business and Entrepreneurship,* 7(3), 296–306.

Sudarmaji, E., Yatim, M. R., Harsono, H., Masrio, H., & Azizah, W. (2024a). Quantifying Drivers of GHG Emissions in ASEAN: Modeling CO2 Emissions Using LMDI and ARIMAX Approaches. *International Journal of Energy Economics and Policy*, 14(6), 426–435. https://doi.org/10.32479/ijeep.17186

Sudarmaji, E., Masrio, H., & Nasip, I. (2024b). Hack the business canvas model based on product-service system: Natural language processing

(NLP) perspective. *Studi Ilmu Manajemen dan Organisasi,* 5(1), 1–17.

Xia, Z., Wu, D., & Zhang, L. (2022). Economic, functional, and social factors influencing electric vehicles' adoption: An empirical study based on the diffusion of innovation theory. *Sustainability,* 14(10), Article 6283. https://doi.org/10.3390/su14106283

Zharova, A., & Lee, H.-E. (2022). Understanding user perception and intention to use smart homes for energy efficiency: A survey study. *Energy Research & Social Science*, 85, Article 102399.