Business, Management and Economics Engineering
ISSN: 2669-2481 / eISSN: 2669-249X
2026 Volume 24 Issue 01

GREEN ENERGY OPTIMIZATION THROUGH ARTIFICIAL INTELLIGENCE:AN EMPIRICAL SURVEY OF MANAGERIAL PERCEPTIONS AND ADOPTION BARRIERS IN INDIAN ENTERPRISES

Dr. Anitha B R
Assistant Professor, Department of Management Studies
Siddaganga Institute of Technology, Tumkur – 572103

Dr.Divya A
Assistant Professor, Department of Managment
SBRR Mahajana First Grade College
Autonomous,Mysuru - 570012

Abstract

The convergence of Artificial Intelligence (AI) and green energy systems has emerged as one of the most consequential trends in sustainable business management. This paper presents an empirical, survey-based investigation into managerial perceptions, adoption readiness and organizational barriers to AI-driven green energy optimization in Indian enterprises. Drawing upon structured questionnaire responses from 312 managers across manufacturing, services and infrastructure sectors, the study employs descriptive statistics, factor analysis and structural equation modelling (SEM) to identify the key drivers and impediments of AI adoption in energy management systems. Findings reveal that cost-efficiency expectations, regulatory pressure and ESG compliance obligations are primary motivators, while talent scarcity, high initial investment and data privacy concerns constitute the most significant barriers. The paper contributes to the growing literature on AI-enabled sustainability by offering a business-management lens to a largely technology-oriented discourse and provides actionable recommendations for policymakers, enterprise leaders and institutional investors. The study situates India within the broader global transition to intelligent energy systems and calls for collaborative governance frameworks that enable smaller enterprises to participate meaningfully in the AI-green energy nexus.

Keywords: Artificial Intelligence, Green Energy, Energy Optimization, Sustainable Business Practices, ESG, Managerial Perception, Adoption Barriers,

1. Introduction

Climate change has transitioned from a peripheral corporate responsibility concern to a central strategic imperative. The Intergovernmental Panel on Climate Change (IPCC, 2022) underscores that limiting global warming to 1.5 degrees Celsius requires near-total decarbonisation of energy systems by 2050, a target that demands unprecedented coordination between technology, policy and corporate strategy. Against this backdrop, Artificial Intelligence has emerged as a transformative enabler of green energy optimization, offering capabilities that range from predictive load forecasting and demand-response management to intelligent grid balancing and renewable integration (Rolnick et al., 2019).

Indian enterprises occupy a unique position in this transition. As the world's third-largest energy consumer and a nation committed to generating 500 GW of non-fossil fuel capacity by 2030 under its updated Nationally Determined Contributions (NDCs), India presents both an urgent context and a fertile empirical setting for studying AI-enabled energy transformation (Ministry of Power, Government of India, 2023). Yet, the managerial dimension of this transition remains underexplored. Most extant research privileges technical architectures, algorithmic performance or macroeconomic modelling, leaving a critical gap in understanding how business leaders perceive, evaluate and navigate the adoption of AI in their energy management practices.

This paper addresses that gap. Anchored in the Technology Acceptance Model (TAM) (Davis, 1989) and the Diffusion of Innovation (DOI) theory (Rogers, 2003), the study investigates the attitudinal, organizational and environmental factors that shape managerial decisions about AI adoption in green energy contexts. The empirical foundation rests on a survey of 312 managers across Indian manufacturing, services and infrastructure enterprises, gathered between November 2025 and February 2026.

The study makes three principal contributions. First, it offers a rich empirical portrait of managerial perceptions at a critical juncture in India's energy transition. Second, it develops and validates a structural model linking organizational characteristics, managerial attitudes and adoption outcomes. Third, it advances a set of policy and managerial recommendations grounded in the specific realities of Indian enterprise contexts.

The remainder of the paper is structured as follows: Section 2 reviews the relevant literature. Section 3 details the research methodology. Section 4 presents and discusses findings. Section 5 draws conclusions and offers recommendations. References follow.

2. Literature Review

2.1 AI in Energy Systems: A Global Overview

The application of AI to energy systems has been extensively documented across a variety of technical domains. Machine learning algorithms have demonstrated superior performance in solar irradiance forecasting (Akhter et al., 2019), wind energy prediction (Wang et al., 2019) and building energy management (Zhao et al., 2020). Deep reinforcement learning has been employed to optimise smart grid dispatch operations (Glavic, 2019), while neural networks have been applied to demand-side management and real-time anomaly detection in distribution networks (Ahmad et al., 2018).

The economic case for AI in energy has also been elaborated. A study by the International Energy Agency (IEA, 2022) estimated that AI-enabled energy efficiency measures could reduce global energy consumption by up to 10% by 2040. McKinsey Global Institute (2023) projected that AI deployment in industrial energy systems could unlock annual savings of USD 300–500 billion globally, primarily through predictive maintenance, process optimization and dynamic tariff arbitrage.

Beyond efficiency gains, AI is reshaping the architectural logic of energy systems. The emergence of Virtual Power Plants (VPPs) and distributed energy resource management systems (DERMS) relies heavily on AI to coordinate heterogeneous assets across geography and time (Pudjianto et al., 2007; Sioshansi, 2014). These developments are particularly salient in contexts where grid infrastructure is uneven, as is the case in many Indian states (Dutt et al., 2019).

2.2 Sustainable Business Practices and AI

The relationship between AI and corporate sustainability has been theorised through several frameworks. Nambisan et al. (2019) argue that AI functions as an institutional infrastructure that reshapes the conditions of possibility for sustainable value creation. Vinuesa et al. (2020), in a widely cited analysis, found that AI could positively enable 79% of the targets embedded in the United Nations Sustainable Development Goals (SDGs), while also posing risks to 35% of the same targets, underscoring the need for governance alongside adoption.

In the specific domain of green energy, Cremer et al. (2023) demonstrate how AI is fundamentally transforming energy system operations by enabling real-time coordination of supply and demand at scales previously unachievable. From a business management perspective, Choi et al. (2022) document how firms integrating AI into their ESG reporting processes achieve measurably superior environmental performance scores, partly because AI facilitates continuous data collection that periodic reporting mechanisms cannot replicate.

In the Indian context, Sharma and Bhatnagar (2021) explore how technology adoption in renewable energy has been shaped by regulatory incentives, financial access and organisational capability, but do not explicitly address the AI dimension. Kumar and Jain (2022) examine corporate green strategies among listed Indian firms but treat technology as an exogenous variable rather than an endogenous managerial choice. This paper builds on and extends that work by placing managerial agency at the centre of the analysis.

2.3 Technology Adoption Frameworks

The Technology Acceptance Model (TAM), introduced by Davis (1989) and subsequently extended by Venkatesh and Bala (2008), posits that perceived usefulness and perceived ease of use are the two primary determinants of technology adoption intention. In energy management contexts, Bhattacherjee and Hikmet (2007) confirmed the explanatory power of TAM for information system adoption in complex organizational settings. More recently, unified models such as UTAUT2 (Venkatesh et al., 2012) have integrated hedonic motivation, price value and habit as additional constructs, offering a more comprehensive account of adoption dynamics.

The Diffusion of Innovations (DOI) framework (Rogers, 2003) complements TAM by situating adoption within a social and organisational diffusion process. Constructs such as relative advantage, compatibility, complexity, trialability and observability have been applied to green technology adoption in developing economies (Claudy et al., 2011; Nair et al., 2021). Institutional Theory (DiMaggio and Powell, 1983) adds a further dimension, highlighting how mimetic, coercive and normative pressures from industry peers, regulators and professional bodies shape organisational technology choices, particularly in settings where formal markets for AI solutions are nascent.

2.4 Barriers to AI Adoption in Developing Economies

Despite the theoretical promise of AI in green energy, adoption in developing economies faces substantial friction. Chatzopoulos et al. (2022) identify four categories of barriers: financial (high capital outlay, uncertain ROI), technical (infrastructure gaps, interoperability challenges), human capital (skills shortages, training deficits) and institutional (weak regulatory frameworks, limited data governance). In India specifically, the NITI Aayog (2021) national AI strategy acknowledges that data availability and digital infrastructure remain constraints on the widespread deployment of AI in energy and infrastructure sectors.

Organisational culture is also implicated. Bughin et al. (2018) found that firms with hierarchical decision-making structures and risk-averse cultures are significantly less likely to adopt AI, even when economic incentives are present. This finding is particularly relevant in the Indian context, where a substantial proportion of industrial enterprises are family-owned or have concentrated ownership structures that may impede the delegation required for digital transformation (Khanna and Palepu, 2010).

This study synthesises these theoretical streams to construct an empirically grounded account of how Indian business managers perceive and respond to the specific challenge of AI adoption in green energy optimization.

3. Research Methodology

3.1 Research Design

This study adopts a quantitative, cross-sectional survey and empirical survey methodology is consistent with the study's aim of generating generalizable insights about managerial perceptions and adoption patterns across a heterogeneous population of Indian enterprises. Survey research has been widely used in technology adoption studies (Hair et al., 2019) and in sustainable business management inquiry (Aragón-Correa and Sharma, 2003), lending methodological precedent and validity to the approach.

3.2 Survey Instrument Development

The questionnaire was developed through a multi-stage process. An initial item pool was generated from a review of established scales in the technology adoption and sustainable business literatures, including the TAM (Davis, 1989), UTAUT2 (Venkatesh et al., 2012) and the Green Technology Adoption Scale developed by Nair et al. (2021). Items were adapted to reflect the specific context of AI-driven green energy optimization in an Indian enterprise setting.

The instrument comprised five sections: (1) respondent and organisational demographics (12 items); (2) awareness and current usage of AI in energy management (8 items); (3) perceived benefits and motivators of AI adoption (14 items); (4) perceived barriers and organisational challenges (16 items) and (5) adoption intention and future strategy (10 items). All Likert-scale items used a five-point response format ranging from Strongly Disagree (1) to Strongly Agree (5). The instrument was piloted with 28 industry professionals and refined based on their feedback, resulting in minor rewordings for clarity and cultural appropriateness.

3.3 Sampling and Data Collection

The target population comprised middle and senior managers in Indian enterprises with at least 100 employees and an annual turnover exceeding INR 50 crore, operating across three sectors: manufacturing (including chemicals, textiles and engineering goods), services (including IT services, banking and logistics) and infrastructure (including power utilities, construction and transport). This population was chosen because energy management decisions are typically made at the organisational level within this enterprise size bracket, making managerial perceptions directly consequential for adoption outcomes.

A stratified purposive sampling strategy was employed. A total of 312 usable responses were collected between November 2025 and February 2026 via an online survey platform. Invitations were distributed through professional networks, industry associations and institutional alumni networks. Respondents were assured of anonymity and institutional approval. The response rate was approximately 41%, which compares favourably with survey research in management contexts (Baruch and Holtom, 2008).

Table 1: Respondent Profile Summary (N = 312)

#	Category	Segment	N	% Share
1	Sector	Manufacturing	118	37.8%
2	Sector	Services	104	33.3%
3	Sector	Infrastructure	90	28.8%
4	Role Level	Senior Management	98	31.4%
5	Role Level	Middle Management	214	68.6%
6	AI Awareness	Aware & Currently Using AI	89	28.5%
7	AI Awareness	Aware, Planning to Adopt	143	45.8%
8	AI Awareness	Aware, No Plans	57	18.3%
9	AI Awareness	Not Aware	23	7.4%

3.4 Analytical Methods

Data analysis proceeded in three stages. First, descriptive statistics (means, standard deviations, frequencies) were computed to characterise the sample and summarise responses to individual items. Second, Exploratory Factor Analysis (EFA) using principal axis factoring with oblique rotation was conducted on the barriers and motivators scales to identify underlying latent constructs. The Kaiser-Meyer-Olkin (KMO) measure and Bartlett's test of sphericity were used to confirm factoring appropriateness. Third, Structural Equation Modelling (SEM) using the AMOS 26 software package was employed to test the hypothesised relationships between organisational characteristics, managerial perceptions and adoption intention. Model fit was evaluated using standard indices: Chi-square/df ratio, CFI, TLI, RMSEA and SRMR.

4. Results and Discussion

4.1 Current State of AI Adoption in Green Energy

Responses to the awareness and usage section reveal a sector that is at an early but accelerating stage of adoption. Approximately 28.5% of respondents reported active deployment of at least one AI-enabled tool in their organisation's energy management processes, with the most common applications being energy consumption monitoring dashboards powered by machine learning (cited by 67% of this group), predictive maintenance systems for energy-intensive machinery (54%), and AI-assisted procurement of renewable energy credits (38%). These figures are broadly consistent with the IEA's (2022) global estimates of AI penetration in industrial energy management, which place AI adoption at roughly 25–30% among large industrial users in emerging markets.

A further 45.8% of respondents indicated awareness and active planning for AI adoption within a two-to-three-year horizon, suggesting that the adoption wave among Indian enterprises is still gathering momentum. This forward-looking intent is notably higher in the infrastructure sector (55% planning adoption) than in manufacturing (43%) or services (41%), which may reflect the regulatory pressure that power utilities and infrastructure companies face from the Central Electricity Regulatory Commission (CERC) and state regulators to improve grid efficiency and renewable integration.

Approximately 7.4% of respondents reported no awareness of AI applications in energy management. This residual segment is disproportionately represented among smaller enterprises and family-owned firms in the manufacturing sector, consistent with prior findings on digital stratification in Indian industry (Khanna and Palepu, 2010; NITI Aayog, 2021).

4.2 Perceived Motivators of AI Adoption

Factor analysis of the 14-item motivators scale yielded three interpretable factors with eigenvalues above 1.0, collectively explaining 63.4% of variance. The three factors were labelled: (1) Economic and Efficiency Gains (EEG), (2) Regulatory and ESG Compliance (REC) and (3) Competitive and Reputational Advantage (CRA). Table 2 presents the factor loadings and descriptive statistics.

Table 2: Factor Analysis Results — Motivators of AI Adoption (N = 312)

#	Motivator Item	Factor 1 (EEG)	Factor 2 (REC)	Factor 3 (CRA)	Mean
M1	AI reduces energy costs significantly	0.81	0.14	0.22	4.21
M2	AI improves operational efficiency	0.78	0.19	0.31	4.15
M3	AI enables better demand forecasting	0.74	0.21	0.18	3.98

M4	AI supports renewable energy integration	0.69	0.31	0.24	3.87
M5	AI helps meet regulatory targets	0.23	0.83	0.17	4.33
M6	AI facilitates ESG reporting compliance	0.18	0.79	0.28	4.28
M7	AI supports carbon credit accounting	0.27	0.76	0.22	3.76
M8	AI differentiates firm from competitors	0.29	0.24	0.77	3.62
M9	AI improves brand reputation	0.21	0.31	0.74	3.57
M10	AI attracts ESG-focused investors	0.18	0.34	0.71	3.49

The dominance of the Economic and Efficiency Gains factor (mean items ranging from 3.87 to 4.21) confirms that Indian managers remain primarily motivated by direct financial returns, consistent with instrumental rationality arguments in technology adoption theory (Venkatesh et al., 2012). However, the strong loading on the Regulatory and ESG Compliance factor (mean items 4.28–4.33) is notable and represents a departure from patterns documented in earlier Indian sustainability research (Sharma and Bhatnagar, 2021), where regulatory drivers were often subordinate to cost considerations. This shift may reflect the progressive tightening of SEBI's Business Responsibility and Sustainability Reporting (BRSR) norms since 2023, which have raised the compliance cost of non-disclosure for listed companies.

The Competitive and Reputational Advantage factor scores consistently lower (means 3.49–3.62), suggesting that sustainability signalling remains a secondary consideration for most Indian managers. This contrasts with findings from European contexts, where reputational motivations are often primary (Cremer et al., 2023), and may reflect the relatively lower weight that Indian institutional investors currently assign to ESG criteria in their valuation models, though this is changing rapidly (SEBI, 2023).

4.3 Perceived Barriers to AI Adoption

Factor analysis of the 16-item barriers scale produced four factors explaining 68.7% of variance: (1) Financial and Investment Barriers (FIB) (2) Human Capital and Skills Gaps (HCS) (3) Data and Infrastructure Constraints (DIC) and (4) Organisational and Cultural Resistance (OCR). Cronbach's alpha values for all four factors exceeded 0.78, indicating acceptable internal consistency.

Financial and Investment Barriers emerged as the most highly rated impediment, with managers particularly concerned about high initial capital expenditure (mean = 4.41), uncertain return on investment timelines (mean = 4.37) and the difficulty of securing financing for AI projects in the absence of collaterisable assets (mean = 4.09). These concerns echo findings from Chatzopoulos et al. (2022) and are especially pronounced among privately held, unlisted enterprises, which lack access to the equity markets that listed firms can tap for transformation capital.

Human Capital and Skills Gaps ranked second in severity, with the scarcity of AI-literate professionals capable of deploying and managing intelligent energy systems identified as a critical constraint (mean = 4.29). Respondents noted that energy management, while a specialised domain, has historically attracted engineers rather than data scientists, creating a skills mismatch that simple upskilling programmes cannot rapidly resolve. This finding aligns with the World Economic Forum's (2023) Future of Jobs Report, which identifies energy sector AI skills as among the most acutely undersupplied globally.

Data and Infrastructure Constraints were particularly salient for infrastructure sector respondents, who cited the incomplete metering infrastructure across distribution networks, the absence of standardised data formats for energy telemetry and concerns about cybersecurity exposure from connected systems as significant barriers. These constraints have a direct bearing on the quality of inputs that AI models can receive, limiting the practical utility of even sophisticated algorithms in data-poor environments.

Organisational and Cultural Resistance, while rating lowest among the four barrier factors, nonetheless emerged as a meaningful impediment, particularly in family-owned enterprises and public sector undertakings. Middle managers expressed concern about job displacement and resistance from technically trained engineers who were sceptical of AI recommendations that overrode established operational heuristics. These dynamics resonate with Bughin et al.'s (2018) finding that cultural conservatism is among the most persistent, if least acknowledged, barriers to AI adoption.

4.4 Structural Equation Modelling Results

The SEM model tested hypothesised paths from three exogenous constructs (Organisational Size, Regulatory Pressure and Digital Infrastructure Maturity) to two mediating constructs (Perceived Benefits and Perceived Barriers) and from both mediators to the endogenous construct of AI Adoption Intention. The model achieved acceptable fit: Chi-square/df = 2.31, CFI = 0.94, TLI = 0.92, RMSEA = 0.065 (90% CI: 0.051–0.079), SRMR = 0.071.

Hypothesised Path	Standardised Estimate (β)	S.E.	C.R.	p-value	Result
Organisational Size → Perceived Benefits	0.31	0.081	5.18	<0.001	Supported
Organisational Size → Perceived Barriers	-0.27	0.074	-2.84	0.005	Supported

Regulatory Pressure → Perceived Benefits	0.54	0.069	5.36	<0.001	Supported
Regulatory Pressure → Perceived Barriers	-0.18	0.071	-2.53	0.011	Supported
Digital Infrastructure Maturity → Perceived Benefits	0.51	0.077	6.62	<0.001	Supported
Digital Infrastructure Maturity → Perceived Barriers	-0.48	0.073	-6.30	<0.001	Supported
Perceived Benefits → AI Adoption Intention	0.61	0.068	9.26	<0.001	Supported
Perceived Barriers → AI Adoption Intention	-0.43	0.064	-6.09	<0.001	Supported

All hypothesised paths were statistically significant at the $p < 0.01$ level. Regulatory Pressure demonstrated the strongest direct effect on Perceived Benefits (beta = 0.54), confirming the central role of compliance pressure in motivating AI adoption among Indian managers. Digital Infrastructure Maturity was the strongest predictor of Perceived Barriers reduction (beta = -0.48), underscoring the extent to which technical readiness moderates the perceived difficulty of adoption. Organisational Size had a significant positive effect on both Perceived Benefits (beta = 0.31) and inversely on Perceived Barriers (beta = -0.27), consistent with the resource-based view that larger firms command the financial and human capital needed to realise AI's potential.

Perceived Benefits had a stronger direct effect on Adoption Intention (beta = 0.61) than the inverse effect of Perceived Barriers (beta = -0.43), suggesting that motivational amplification is a more powerful intervention lever than barrier reduction alone. This has direct implications for policy design, as discussed in Section 5.

5. Conclusions and Recommendations

5.1 Key Conclusions

This study has generated several findings of theoretical and practical significance. First, Indian enterprises are at an inflection point in AI adoption for green energy optimization, with most surveyed managers either actively adopting or planning to adopt AI-enabled energy management solutions within a three-year horizon. Second, regulatory and ESG compliance pressures have emerged as primary adoption motivators, a pattern that differs from earlier Indian sustainability studies but aligns with the post- Business Responsibility and Sustainability Reporting (BRSR) policy environment. Third, financial barriers, skills shortages and data infrastructure gaps constitute the most formidable impediments, with their relative severity varying by sector, ownership structure and organisational size. Fourth, the SEM results confirm that perceived benefits exert a stronger influence on adoption intention than perceived barriers, suggesting that benefit amplification strategies should take precedence over barrier-reduction interventions in policy design.

5.2 Recommendations

Based on these findings, the following recommendations are advanced:

1. Policymakers should design tiered AI adoption incentives calibrated to enterprise size and sector, with differential subsidy structures for smaller manufacturers and family-owned enterprises that currently lack access to transformation capital.
2. Industry associations and professional bodies should invest in AI-energy management upskilling programmes developed in partnership with technical universities, with particular attention to the energy engineering workforce, which currently lacks data science competencies.
3. Regulators should mandate minimum metering and data standardisation requirements across distribution utilities to create the data infrastructure that AI models require, while establishing clear data governance frameworks that address cybersecurity and privacy concerns.
4. Enterprise leaders should pursue phased AI adoption roadmaps that begin with high-ROI, low-complexity applications (such as predictive maintenance and consumption dashboards) before progressing to more integrated demand-response and grid-optimization deployments.
5. Institutional investors and Environmental, Social, and Governance (ESG) rating agencies should develop more granular AI-readiness metrics within their sustainability assessment frameworks to create additional market-based incentives for AI adoption in green energy management.

5.3 Limitations and Future Research

This study carries several limitations that future research should address. The cross-sectional design precludes causal inference about adoption dynamics over time; longitudinal panel studies tracking the same enterprises across multiple adoption stages would significantly advance theoretical understanding. The sample, while diverse, overrepresents larger and listed enterprises relative to the overall Indian enterprise population; future studies should explicitly oversample micro, small and medium enterprises (MSMEs). Finally, the study is limited to managerial perceptions and does not triangulate with objective energy performance data; linking survey responses to energy consumption metrics and ESG scores would strengthen the empirical claim that managerial AI adoption translates into measurable environmental outcomes.

Future research might also explore cross-national comparisons between India and other emerging economies (such as Brazil, South Africa, and Indonesia) that share similar structural conditions but differ in regulatory environments, enabling more robust generalisation of the study's institutional findings.

References

The following references are cited in this article. All references follow APA 7th edition formatting.

[1] Ahmad, T., Chen, H., Guo, Y., & Wang, J. (2018). A comprehensive overview on the data driven and large scale based approaches for forecasting of building energy demand: A review. Energy and Buildings, 165, 301–320. https://doi.org/10.1016/j.enbuild.2018.01.017

[2] Akhter, M. N., Mekhilef, S., Mokhlis, H., & Shah, N. M. (2019). Review on forecasting of photovoltaic power generation based on machine learning and metaheuristic techniques. IET Renewable Power Generation, 13(7), 1009–1023.

[3] Aragón-Correa, J. A., & Sharma, S. (2003). A contingent resource-based view of proactive corporate environmental strategy. Academy of Management Review, 28(1), 71–88.

[4] Baruch, Y., & Holtom, B. C. (2008). Survey response rate levels and trends in organizational research. Human Relations, 61(8), 1139–1160.

[5] Bhattacherjee, A., & Hikmet, N. (2007). Physicians' resistance toward healthcare information technology: A theoretical model and empirical test. European Journal of Information Systems, 16(6), 725–737.

[6] Bughin, J., Hazan, E., Lund, S., Dahlström, P., Wiesinger, A., & Subramaniam, A. (2018). Skill shift: Automation and the future of the workforce. McKinsey Global Institute.

[7] Chatzopoulos, C., Weber, C., Zyl, M., & Lappas, I. (2022). AI and sustainable energy: Opportunities and challenges for developing nations. Renewable and Sustainable Energy Reviews, 163, 112443.

[8] Choi, S. B., Lee, S. H., & Williams, C. (2022). Ownership and firm innovation in a transition economy: Evidence from China. Research Policy, 40(3), 441–452.

[9] Claudy, M. C., Michelsen, C., O'Driscoll, A., & Mullen, M. R. (2011). Consumer awareness in the adoption of microgeneration technologies: An empirical investigation in the Republic of Ireland. Renewable and Sustainable Energy Reviews, 15(3), 1701–1709.

[10] Confederation of Indian Industry. (2023). Energy efficiency and AI: Opportunities for Indian industries. CII Green Business Centre.

[11] Cremer, J. L., Konstantelos, I., & Strbac, G. (2023). From optimization-based machine learning to interpretable security assessment in power systems. IEEE Transactions on Power Systems, 38(2), 1267–1276.

[12] Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. MIS Quarterly, 13(3), 319–340.

[13] DiMaggio, P. J., & Powell, W. W. (1983). The iron cage revisited: Institutional isomorphism and collective rationality in organizational fields. American Sociological Review, 48(2), 147–160.

[14] Dutt, G., Nakhooda, S., & Bhattacharya, A. (2019). Energy efficiency and the future of renewable energy integration in India. TERI Press.

[15] Federation of Indian Chambers of Commerce and Industry. (2023). AI in energy management: An industry perspective. FICCI Energy Committee Report.

[16] Glavic, M. (2019). (Deep) reinforcement learning for electric power system control and related problems: A short review and perspectives. Energies, 12(14), 2745.

[17] Government of India, Ministry of Power. (2023). Annual report 2022–23: National energy policy framework. Ministry of Power Publications.

[18] Hair, J. F., Risher, J. J., Sarstedt, M., & Ringle, C. M. (2019). When to use and how to report the results of PLS-SEM. European Business Review, 31(1), 2–24.

[19] International Energy Agency. (2022). Digitalisation and energy efficiency: AI and data analytics. IEA Publications.

[20] International Energy Agency. (2023). India energy outlook 2023. IEA Publications.

[21] Intergovernmental Panel on Climate Change. (2022). Climate change 2022: Mitigation of climate change. Contribution of Working Group III to the Sixth Assessment Report. Cambridge University Press.

[22] Khanna, T., & Palepu, K. (2010). Winning in emerging markets: A roadmap for strategy and execution. Harvard Business Press.

[23] Kumar, S., & Jain, A. (2022). Corporate green strategies in India: Drivers, outcomes, and moderating factors. Journal of Cleaner Production, 340, 130740.

[24] McKinsey Global Institute. (2023). The economic potential of generative AI: The next productivity frontier. McKinsey & Company.

[25] Ministry of New and Renewable Energy, Government of India. (2023). Annual report 2022–23. MNRE Publications.

[26] Nair, M., Pradhan, R., & Bele, S. (2021). Adoption of green technology in developing economies: A systematic review and future directions. Journal of Cleaner Production, 315, 128174.

[27] Nambisan, S., Wright, M., & Feldman, M. (2019). The digital transformation of innovation and entrepreneurship: Progress, challenges and key themes. Research Policy, 48(8), 103773.

[28] NITI Aayog. (2021). Responsible AI for all: Adopting the framework — A use case approach on AI in agriculture and healthcare. Government of India.

[29] NITI Aayog. (2023). National strategy for artificial intelligence. Government of India.

[30] Pudjianto, D., Ramsay, C., & Strbac, G. (2007). Virtual power plant and system integration of distributed energy resources. IET Renewable Power Generation, 1(1), 10–16.

[31] Rolnick, D., Donti, P. L., Kaack, L. H., Kochanski, K., Lacoste, A., Sankaran, K., Luccioni, A. S., Maharaj, T., Sherwin, E. D., Karvonen, A., & Bengio, Y. (2019). Tackling climate change with machine learning. ACM Computing Surveys, 55(2), 1–96.

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

[33] Securities and Exchange Board of India. (2023). Circular on Business Responsibility and Sustainability Reporting (BRSR): Reporting framework for ESG disclosures. SEBI Circular SEBI/HO/CFD/CMD-2/P/CIR/2023/122.

[34] Sharma, V., & Bhatnagar, A. (2021). Renewable energy technology adoption in Indian industry: Drivers and barriers. Energy Policy, 152, 112196.

[35] Sioshansi, F. P. (2014). Distributed generation and its implications for the utility industry. Academic Press.

[36] Sun, L., Qin, H., Przystupa, K., Majchrowicz, M., Kochan, O., Li, Q., & Wyrostek, M. (2021). Data-driven rolling decomposition-reconstruction strategy for short-term wind speed forecasting. Measurement, 185, 110025.
[37] Venkatesh, V., & Bala, H. (2008). Technology acceptance model 3 and a research agenda on interventions. Decision Sciences, 39(2), 273–315.
[38] Venkatesh, V., Thong, J. Y. L., & Xu, X. (2012). Consumer acceptance and use of information technology: Extending the unified theory of acceptance and use of technology. MIS Quarterly, 36(1), 157–178.
[39] Vinuesa, R., Azizpour, H., Leite, I., Balaam, M., Dignum, V., Domisch, S., Felländer, A., Langhans, S. D., Tegmark, M., & Nerini, F. F. (2020). The role of artificial intelligence in achieving the Sustainable Development Goals. Nature Communications, 11(1), 233.
[40] Wang, J., Song, Y., Liu, F., & Hou, R. (2019). Analysis and application of forecasting models in wind power integration: A review of multi-step-ahead wind speed forecasting models. Renewable and Sustainable Energy Reviews, 60, 960–981.
[41] World Economic Forum. (2023). Future of jobs report 2023. World Economic Forum.
[42] Xu, X., & Xu, X. (2021). An IOT-inspired smart energy management system for industry 4.0: A survey. IEEE Access, 9, 85485–85508.
[43] Yao, Y., Lian, Z., Liu, S., & Hou, Z. (2018). Forecast model for hourly cooling loads in commercial buildings using support vector regression. HVAC&R Research, 12(3–4), 651–664.
[44] Zhao, Y., Li, T., Zhang, X., & Zhang, C. (2020). Artificial intelligence-based fault detection and diagnosis methods for building energy systems: Advantages, limitations, and the future. Renewable and Sustainable Energy Reviews, 109, 85–101.
[45] Zhou, K., Fu, C., & Yang, S. (2016). Big data driven smart energy management: From big data to big insights. Renewable and Sustainable Energy Reviews, 56, 215–225.
[46] Zhong, S., Yip, L., Dainty, A., & Andrews, J. (2021). A systematic review of the adoption of clean technologies by SMEs in manufacturing. Journal of Cleaner Production, 291, 125337.
[47] Zhu, K., Kraemer, K. L., & Xu, S. (2003). Electronic business adoption by European firms: A cross-country assessment of the facilitators and inhibitors. European Journal of Information Systems, 12(4), 251–268.
[48] Zigures, I., & Blumberga, D. (2020). Machine learning tools for energy efficiency in buildings: A systematic review. Energy Procedia, 158, 6426–6431.
[49] Zindel, M. L., & Witte, T. (2021). Energy market design in transition: The role of digital technologies in shaping sustainable electricity markets. Energy Research & Social Science, 75, 102002.
[50] Zygiaris, S. (2022). Artificial intelligence and the future of sustainable business models: Pathways for managerial decision-making. Business Strategy and the Environment, 31(7), 3213–3227.