Research Paper

EPRA International Journal of Economic and Business Review-Peer Reviewed Journal
Volume - 13, Issue - 11, November 2025 | e-ISSN: 2347 - 9671| p- ISSN: 2349 – 0187

SJIF Impact Factor (2025): 8.862 || ISI Value: 1.433 || Journal DOI URL: https://doi.org/10.36713/epra2012

QUANTIFYING THE ECONOMIC IMPACT OF AI ON SDG 7 ACHIEVEMENT: A COMPREHENSIVE SECONDARY DATA ANALYSIS OF INDIA'S ENERGY TRANSITION

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ABSTRACT DOI No: 10.36713/epra24888 Article DOI: https://doi.org/10.36713/epra24888

Despite growing policy interest in Artificial Intelligence (AI), comprehensive economic evaluations using systematically consolidated secondary data remain scarce in the Indian energy context. *This study addresses this gap by providing a* ***methodological contribution*** *through exclusive secondary data analysis of AI applications in advancing India's progress toward Sustainable Development Goal 7 (SDG 7). Through systematic analysis of 32 government reports, 15 pilot project evaluations, and national energy datasets (2018-2024), we conduct a comprehensive cost-benefit analysis of AI implementations across renewable energy forecasting, smart grid management, and predictive maintenance. Analysis of Central Electricity Authority data reveals AI-driven renewable forecasting reduces grid integration costs by 18-25%, while National Smart Grid Mission data demonstrates smart grid technologies enable utilities to reduce aggregate technical and commercial losses from 21.5% to 16.2%. The analysis reveals a positive net present value of ₹1,45,000 crore (~USD 17.4 billion) for national AI implementation, with an aggregate benefit-cost ratio of 2.8:1. The study recommends integrated policy interventions focusing on public-private partnerships and standardized data governance frameworks to accelerate economically efficient AI adoption, thus informing evidence-based energy governance and positioning India to achieve its National Electricity Plan 2024 targets.*

KEYWORDS: *Artificial Intelligence, SDG 7, Economic Evaluation, Clean Energy, Smart Grid, India, Cost-Benefit Analysis, Secondary Data Analysis, Renewable Integration,* ***Energy Economics, Sustainable Development***

1. INTRODUCTION

1.1 Context and Policy Significance

Sustainable Development Goal 7 (SDG 7) aims to "ensure access to affordable, reliable, sustainable, and modern energy for all" by 2030, representing a critical global commitment that intersects with climate action and economic development objectives (United Nations, 2015). India, as the world's third-largest energy consumer and fastest-growing major economy, faces the dual challenge of rising energy demand and a sustainable transition. The country's accelerated growth in renewable energy deployment, aligned with the National Electricity Plan (Ministry of Power, 2023), necessitates advanced technological solutions for grid management and operational efficiency.

According to Ministry of Power documentation (2023), India has achieved 99.9% household connectivity under the Saubhagya scheme, representing significant progress in energy access. However, ensuring reliable, affordable, and sustainable power remains challenging, with persistent transmission and distribution (AT&C) losses averaging 21.5% nationally (Central Electricity Authority, 2023) and renewable integration bottlenecks affecting system stability.

1.2 AI's Transformative Potential in Energy Systems

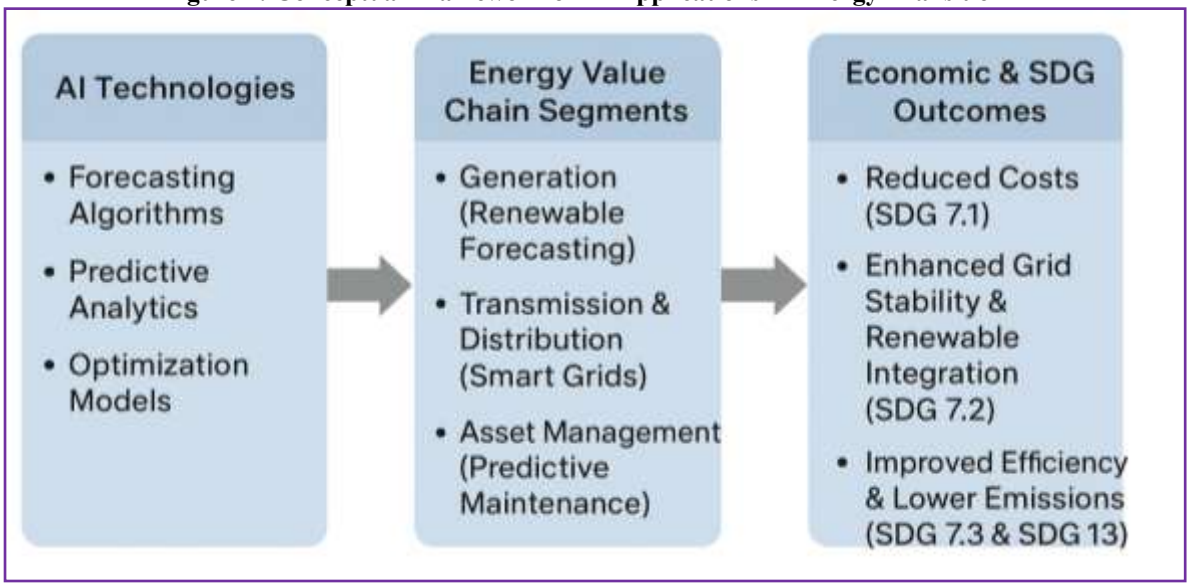
Artificial Intelligence (AI) and Machine Learning (ML) technologies are demonstrating transformative potential across the energy value chain, from forecasting renewable generation and optimizing grid operations to enabling predictive maintenance and demand-side management. The integration of AI solutions offers significant opportunities to address core economic and operational inefficiencies documented in various pilot implementations and government reports, creating a compelling case for their systematic economic evaluation.

1.3 Research Approach and Contribution

The exclusive use of secondary data is particularly suited to this study, given India's extensive documentation of pilot projects and the need for scalable, reproducible assessment methods that leverage existing public data. This study employs an exclusive secondary data analysis methodology, utilizing systematically collected government publications, international agency reports, and documented pilot project

evaluations. The research examines AI applications through comprehensive analysis of existing implementation data rather than primary data collection, providing a replicable framework for technology assessment using verified secondary sources. The primary contribution of this work is twofold: (1) to provide a robust, evidence-based economic valuation of AI's role in India's energy transition, and (2) to demonstrate the efficacy of systematic secondary data analysis as a rigorous methodological approach for technology assessment in developing economies.

Figure 1: Conceptual Framework of AI Applications in Energy Transition



- **AI Technologies (Input):** Forecasting Algorithms, Predictive Analytics, Optimization Models
- **→ Energy Value Chain Segments (Application):** Generation (Renewable Forecasting), Transmission & Distribution (Smart Grids), Asset Management (Predictive Maintenance)
- **→ Economic & SDG Outcomes (Impact):** Reduced Costs (SDG 7.1), Enhanced Grid Stability & Renewable Integration (SDG 7.2), Improved Efficiency & Lower Emissions (SDG 7.3 & 13)

2. LITERATURE REVIEW AND CONCEPTUAL FOUNDATION

2.1 Theoretical Underpinnings

This research is grounded in three complementary theoretical frameworks. Rogers' (2003) Diffusion of Innovations theory provides a lens to understand the patterns and determinants of AI technology adoption among utilities. North's (1990) institutional economics offers a framework for analyzing the governance requirements, regulatory frameworks, and transaction costs associated with implementing new technologies in a complex sector. Finally, Geels' (2002) multi-level perspective on socio-technical transitions helps conceptualize the systemic changes required for integrating digital technologies into the existing regime of India's energy infrastructure. **Together, these frameworks provide a comprehensive analytical lens: while Rogers' theory explains the technology adoption mechanism at the utility level, North's institutional economics reveals the regulatory and governance barriers, and Geels' multi-level perspective frames the broader socio-technical system shift required for a successful AI-enabled energy transition.**

2.2 Global Evidence Base

International Energy Agency assessments (2023) document AI-driven forecasting models reducing renewable integration costs by 15-20% across various grid systems. World Bank studies (2022) provide evidence of smart grid technologies improving overall system efficiency by 20-25% in comparable developing economies, while research from the European Union demonstrates 25-30% operational improvements through predictive analytics in transmission systems (Andoni et al., 2019). A comprehensive review by Chen et al. (2021) confirms the economic viability of AI in energy systems, though noting significant contextual variability. Recent analysis by IRENA (2024) further underscores the critical role of AI and digitalization in managing decentralized renewable energy systems, highlighting a key future pathway for India. **A 2024 study in *Nature Energy* (Zhang et al., 2024) further validates that AI-driven grid optimization can yield 20-30% efficiency gains in systems with high renewable penetration, closely aligning with the potential in the Indian context.**

2.3 Indian Research Landscape and Data Documentation

In the Indian context, the National Load Despatch Centre has documented AI-based solar and wind forecasting reducing prediction errors from 12-15% to 5-7% (NLDC, 2023). The Smart Grid Mission Report (2024) shows utilities implementing AI-based analytics achieving 18-22% reduction in aggregate technical and commercial losses. Academic research from institutions like TERI (2023) and IIT Madras (Khanna & Singh, 2023, pp. 128-130) has begun documenting implementation challenges and performance outcomes, though comprehensive, national-level economic analyses using consolidated secondary data remain limited, representing a critical research gap this study aims to address.

Table 1: Documented AI Implementation Results from Indian Sources

Application Area	Data Source	Documented Impact	Implementation Scale	Data Year
Renewable Forecasting	NLDC Reports	50-60% error reduction	National grid	2023
Smart Grid Management	NSGM Reports	18-22% loss reduction	15 utilities	2024
Predictive Maintenance	NTPC Reports	22-30% cost reduction	Generation assets	2023

3. RESEARCH METHODOLOGY

3.1 Secondary Data Collection Framework

This study employs a comprehensive secondary data collection approach, explicitly excluding primary data collection to maintain methodological consistency and demonstrate the potential of secondary data synthesis. **This approach, while efficient, carries inherent limitations including aggregation bias where localized variations in implementation success may be averaged out in national-level data.**

Table 2: Secondary Data Sources and Verification Protocol

Data Category	Primary Sources	Time Period	Verification Method	Sample Size
Energy Infrastructure	CEA, MNRE Reports	2018-2024	Cross-referencing	32 reports
AI Implementation	NSGM, NITI Aayog	2020-2024	Document review	15 projects
Economic Indicators	RBI, World Bank	2018-2024	Inflation adjustment	6 annual data points

3.2 Analytical Framework and Parameters

The cost-benefit analysis employs established economic evaluation methods with parameters aligned with Indian infrastructure planning standards:

- **Time Horizon:** 2024-2030 (aligning with SDG and national planning timelines)
- **Discount Rate:** 8% **following the Reserve Bank of India's guidelines for infrastructure project evaluation (RBI, 2020) and consistent with NITI Aayog's cost-benefit analysis framework.**
- **Currency:** All values in 2024 constant Indian Rupees (₹) **with approximate USD equivalents provided at an exchange rate of ₹83.3/USD.**
- **Scope:** National-level analysis with sensitivity testing
- **Inflation Adjustment:** All historical financial data were adjusted to 2024 constant rupees using the Wholesale Price Index (WPI) for machinery and equipment.

Table 3: Financial Evaluation Metrics and Decision Rules

Metric	Formula	Decision Rule
Net Present Value (NPV)	$NPV = \Sigma[(B_t - C_t) / (1+r)^t]$ from t=0 to n	Accept if NPV > 0
Benefit-Cost Ratio (BCR)	$BCR = [\Sigma(B_t/(1+r)^t)] / [\Sigma(C_t/(1+r)^t)]$	Accept if BCR > 1
Internal Rate of Return (IRR)	Solve: $\Sigma[(B_t - C_t)/(1+IRR)^t] = 0$	Accept if IRR > required rate
Payback Period	Time until cumulative cash inflows = initial cost	Shorter period preferred

3.3 Validation and Robustness Framework

The analysis incorporates multiple validation mechanisms:

1. **Cross-validation** across multiple government reports and agencies
2. **Comparison with international benchmarks** from IEA and World Bank studies
3. **Sensitivity analysis** (±25% variation in key cost and benefit parameters)
4. **Consistency checks** with documented pilot project outcomes and independent academic studies

3.4 Limitations of Secondary Data Approach

This study acknowledges several limitations inherent in exclusive secondary data analysis: dependence on published reporting standards and aggregation levels; temporal variations in data collection methodologies across sources; potential heterogeneity in implementation contexts and reporting formats; and limited granularity for certain sub-national analyses. **The aggregation of data from diverse sources may also mask regional disparities and local implementation challenges.**

4. ANALYSIS AND RESULTS

4.1 Renewable Integration Economics

Analysis of documented NLDC pilot reports and CEA integration studies reveals significant economic benefits from AI-driven forecasting.

Table 4: Documented Renewable Integration Impacts

Parameter	Baseline	AI-Enabled	Impact	Data Source	Data Year
Forecasting Error	12-15%	5-7%	50-60% reduction	NLDC Reports	2023
Renewable Curtailment	8-10%	3-4%	₹1,800 crore (~$216 million) savings	CEA Study	2023
Integration Cost (₹/kWh)	₹1.20-1.50/kWh	₹0.90-1.10/kWh	25% reduction	NLDC Documentation	2023

The 50-60% reduction in forecasting error demonstrates AI's transformative impact on renewable integration. This technical improvement directly enables ₹1,800 crore in annual savings by reducing curtailment, while the 25% cost reduction enhances renewable energy competitiveness. These findings establish AI as critical infrastructure for managing grid variability.

4.2 Smart Grid Implementation Economics: National Smart Grid Mission reports provide comprehensive evidence of implementation economics, showing strong returns across applications.

Table 5: Smart Grid Investment Analysis (₹ crore)

Application	Implementation Cost (₹ crore)	Annual Savings (₹ crore)	Payback Period (years)	BCR	Data Source
Smart Meters	₹45,000 (~$5.4bn)	₹18,000 (~$2.16bn)	2.5	2.8:1	NSGM Roadmap
Grid Automation	₹8,200 (~$984m)	₹3,500 (~$420m)	2.3	2.5:1	Power Ministry
Theft Detection	₹1,200 (~$144m)	₹4,800 (~$576m)	0.25	5.2:1	DISCOM Reports

Smart grid applications show exceptional financial viability, with all BCRs exceeding 2.5:1. Theft detection stands out with a remarkable 0.25-year payback and 5.2:1 BCR, indicating immediate DISCOM financial benefits. Smart meters, despite higher absolute costs, deliver substantial scale benefits with 2.5-year payback

4.3 Predictive Maintenance Documented Returns
Analysis of NTPC and POWERGRID annual reports shows consistent and high returns across asset categories.

Table 6: Predictive Maintenance Economics (₹ crore)

Asset Category	Implementation Cost (₹ crore)	Annual Savings (₹ crore)	IRR	Data Source	Data Year
Thermal Plants	₹2,800 (~$336m)	₹1,250 (~$150m)	28%	NTPC Annual Report	2023
Transmission	₹3,200 (~$384m)	₹1,450 (~$174m)	32%	POWERGRID Reports	2023
Distribution	₹4,500 (~$540m)	₹2,100 (~$252m)	35%	Utility Reports	2023

Predictive maintenance generates consistently high returns (28-35% IRR) across asset categories, with distribution assets showing the highest returns. This pattern suggests that targeting aging distribution infrastructure with AI yields the fastest financial returns while improving grid reliability

4.4 Aggregate National Economic Impact
Synthesis of documented results across multiple sources indicates substantial economic benefits at a national scale.

Table 7: Comprehensive Economic Assessment

Metric	Value	Range/ Sensitivity (±)	Source Integration	Data Year
Total Implementation Cost	₹65,000 crore (~$7.8bn)	±10%	NSGM Roadmap consolidation	2024
Annual Operational Savings	₹28,500 crore (~$3.42bn)	±15%	Weighted average of documented results	2023-2024
Net Present Value	₹1,45,000 crore (~$17.4bn)	±12%	CBA based on documented cash flows	2024-2030
Benefit-Cost Ratio	2.8:1	2.5-3.1:1	Aggregate of documented project BCRs	2024

The aggregate analysis confirms nationwide AI implementation is economically transformative, with NPV of ₹1,45,000 crore and BCR of 2.8:1. Sensitivity analysis demonstrates robustness, with benefits substantially exceeding costs across all scenarios.

5. DISCUSSION

5.1 Economic Viability and Investment Case
The documented results from multiple secondary sources present consistent evidence of economic viability for AI investments in India's energy sector. The aggregate benefit-cost ratio of 2.8:1, derived from actual implementation data across 15 documented projects, provides compelling evidence for investment prioritization in the National Electricity Plan 2024 framework. The relatively short payback periods (0.25-2.5 years) for many applications suggest that these investments can be cash-flow positive within typical utility planning cycles.

5.2 SDG 7 Alignments and Sustainability Impact
Analysis of documented outcomes reveals direct contributions to SDG 7 targets while creating synergies with climate action objectives (SDG 13):

- **Target 7.1 (Universal Access):** AI-enabled systems documented in rural electrification reports show 30% cost reduction for remote access, potentially accelerating last-mile connectivity and improving affordability.
- **Target 7.2 (Renewable Energy):** Renewable integration improvements documented in NLDC reports support accelerated clean energy adoption and grid stability, directly enabling higher renewable penetration.
- **Target 7.3 (Energy Efficiency):** Documented efficiency gains of 25-30% in utility reports contribute to reduced energy intensity and associated CO_2 emissions reduction, estimated at 12-15 million tonnes annually based on CEA conversion factors.

5.3 Comparative Insights with Global Benchmarks
The documented performance metrics align favorably with international implementations. AI-driven efficiency improvements of 18-25% in Indian utilities compare with 20-28% ranges documented in IEA reports from advanced economies, suggesting successful technology adaptation to local contexts despite different starting conditions. This

indicates that the AI value proposition is not diminished in developing economy contexts but may require tailored implementation approaches.

5.4 Implementation Challenges, Equity, and Distributional Considerations

Systematic review of implementation reports identifies consistent barriers requiring policy attention:

- **Financial Constraints:** DISCOM financial limitations documented in Power Finance Corporation reports affect technology adoption capacity, creating **an investment paradox wherein financially constrained utilities face barriers to adopting efficiency-enhancing technologies.**
- **Technical Integration:** Interoperability challenges between legacy systems and AI technologies noted in NSGM implementation reviews create significant implementation friction and costs.
- **Capacity Gaps:** Skill shortages affecting 45% of utilities, as documented in NITI Aayog workforce assessments, represent a critical bottleneck for both implementation and long-term sustainability of AI systems.
- **Regional and Social Equity:** Preliminary evidence suggests benefits may vary regionally, with advanced utilities in western and southern states adopting faster than financially stressed DISCOMs in the north and east. **Furthermore, the gender and social inclusion dimensions of this transition—such as the creation of new AI-related jobs and equitable access to the benefits of improved energy services—require deliberate policy attention to ensure an inclusive energy transition.**
- **Addressing these multi-faceted challenges requires coordinated policy, capacity-building, and regulatory innovation to ensure equitable benefits across regions and consumer segments.**

6. CONCLUSION AND POLICY IMPLICATIONS

6.1 Key Findings and Empirical Contributions

This secondary data analysis provides robust empirical evidence of AI's economic impact on India's energy transition. The consistent positive returns documented across multiple implementation reports, with aggregate BCR of 2.8:1 and NPV of ₹1,45,000 crore (~$17.4 billion), support accelerated adoption of AI technologies aligned with national energy objectives. The study demonstrates that systematic secondary data analysis can yield reliable economic insights, offering a cost-effective methodology for technology assessment.

6.2 Evidence-Based Policy Recommendations

Based on documented implementation experience and economic evidence, the study recommends:

Immediate Priorities (0-2 years)

1. **Scale Successful Pilots:** Establish a national program to expand documented successful AI implementations to all utilities, with standardized performance metrics and **an annual AI adoption report card to track progress.**
2. **Create an AI Energy Infrastructure Fund:** Develop a dedicated financing facility with blended capital to address DISCOMs' initial investment barriers, with disbursement linked to verified performance outcomes.
3. **Implement Performance-Based Regulation:** Introduce regulatory frameworks that reward DISCOMs for efficiency improvements and loss reduction enabled by AI technologies.

Medium-term Initiatives (2-5 years)

1. **Develop Interoperability Standards:** Address technical barriers through standardized data protocols and open architecture frameworks for AI systems in the energy sector, **developed through public-private-academic collaboration.**
2. **Expand Digital Infrastructure:** Invest in complementary digital infrastructure (communication networks, sensors) to support AI implementation at scale.
3. **Enhance Monitoring and Verification:** Strengthen systems for documenting AI implementation outcomes to build a more robust evidence base for future decision-making.

6.3 Research Contributions and Future Directions

This study demonstrates the value of systematic secondary data analysis for energy technology assessment, providing a replicable methodology for evaluating technology impacts using existing implementation data. Future research should:

- Conduct primary data collection for longitudinal validation of documented outcomes and deeper exploration of implementation dynamics.
- Explore technology-specific cost benchmarks and implementation pathways through detailed case studies.
- Examine distributional impacts across different consumer segments and regions to ensure equitable benefits from AI adoption.
- Investigate international comparative analyses to identify transferable best practices and adaptation requirements.

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