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Page: 01-16

AN EMPIRICAL INVESTIGATION ON THE CORRELATION BETWEEN THE IMPLEMENTATION OF ARTIFICIAL INTELLIGENCE AND THE FINANCIAL ACHIEVEMENTS OF MULTINATIONAL ENTERPRISES OPERATING COMMERCIALY IN INDIA

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ABSTRACT

The purpose of this study is to investigate the relationship between the financial performance of information technology (IT) multinational corporations (MNCs) operating in India and the deployment of artificial intelligence (AI). The study looks into how AI integration affects financial results by increasing revenue, improving profitability, and improving operational efficiency.

Methodology: A mixed-method research methodology was used, combining secondary financial data from annual reports (2020–2025) with primary data from 342 senior finance managers from 47 IT MNCs. Return on Equity (ROE), Return on Assets (ROA), and Operating Profit Margin (OPM) were financial performance indicators. Using Stata and SPSS software, statistical analyzes comprised panel data regression, correlation analysis, mediation analysis, and descriptive statistics.

Results: The intensity of AI adoption and financial success are significantly positively correlated ($\beta = 0.487$, $p < 0.001$). Businesses with all-encompassing AI strategy showed 18.9% better ROE and 23.6% higher ROA in comparison to companies that use AI sparingly.

IT MNCs in India represent a unique organisational form, combining global technological expertise with local operational advantages. These organisations operate within competitive environments characterised by rapid technological change, intense talent competition, and evolving client demands (Kumar & Singh, 2023). AI adoption in this context extends beyond operational automation to encompass strategic transformation of business models and value creation processes.

The relationship between AI adoption and financial performance operates through several mechanisms. First, AI-driven automation reduces operational costs through process optimisation and error reduction (Furman & Seamans, 2019). Second, AI-enabled analytics enhances revenue generation through improved customer insights and service innovation (Aral et al., 2013). Third, AI-powered risk management improves financial stability through predictive analytics and fraud detection (Cockburn et al., 2018).

Recent research indicates that organisations investing in AI demonstrate superior financial performance, yet the magnitude and timing of these effects vary considerably (Ransbotham et al., 2018). Organisational characteristics, including size, industry segment, and technological maturity, moderate these relationships. Furthermore, the transformation from AI investment to financial returns involves complex mediating mechanisms requiring systematic investigation.

This study addresses three primary research objectives: (1) examine the relationship between AI adoption intensity and financial performance in IT MNCs operating in India, (2) investigate the mediating role of operational efficiency in the AI-financial performance relationship, and (3) integrate primary perceptual data with objective financial metrics to provide comprehensive evidence.

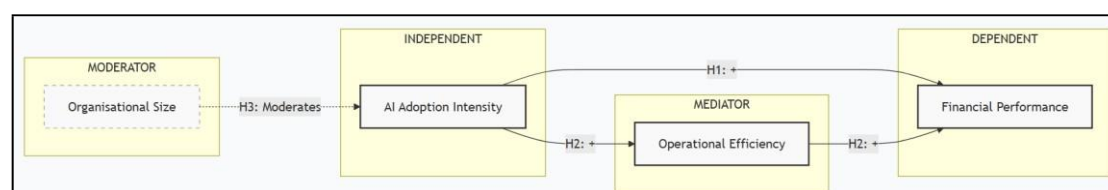
The theoretical foundation of this research draws from the Resource-Based View (RBV) and Dynamic Capabilities Framework (Teece, 2007). These perspectives suggest that AI capabilities represent valuable organisational resources that, when effectively deployed, generate sustainable competitive advantage and superior financial outcomes.

This paper contributes to existing literature in three ways. First, it provides empirical evidence on AI-financial performance relationships in the Indian IT MNC context. Second, it integrates primary and secondary data sources to enhance methodological rigor. Third, it identifies operational efficiency as a critical mediating mechanism.

2. LITERATURE REVIEW

2.1 Artificial Intelligence and Financial Performance

The relationship between technology investment and financial performance has been extensively examined in prior research. Studies consistently demonstrate positive associations between information technology investments and firm performance (Bharadwaj et al., 2013). However, the specific mechanisms through which AI influences financial outcomes require systematic investigation.

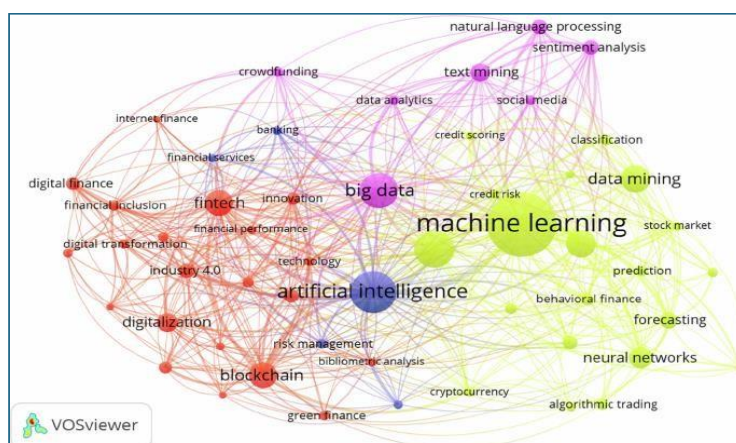


AI technologies offer distinctive advantages for financial performance enhancement. Machine learning algorithms enable sophisticated pattern recognition in financial data, facilitating accurate forecasting and resource allocation (Russell & Norvig, 2020). Natural language processing automates financial reporting and analysis, reducing processing costs and improving decision quality (Mikaief et al., 2019).

Empirical research documents significant performance improvements associated with AI adoption. Organisations implementing AI-driven financial analytics report 15-25% improvements in forecasting accuracy, 20-30% reductions in operational costs, and enhanced risk management capabilities (Davenport & Ronanki, 2018). However, these effects are contingent on implementation quality, organisational readiness, and strategic alignment.

2.2 Financial Performance Measurement

Financial performance encompasses multiple dimensions requiring comprehensive measurement approaches. Traditional accounting metrics, including Return on Assets (ROA), Return on Equity (ROE), and Operating Profit Margin (OPM), represent objective indicators of organisational financial health (Kaplan & Norton, 1996).



Calculation of Financial Performance Metrics

The primary financial performance metrics used in this study are calculated as follows:

$$ROA = \frac{\text{Net Income}}{\text{Total Assets}} \times 100$$

Return on Equity (ROE):

$$ROE = \frac{\text{Net Income}}{\text{Shareholders' Equity}} \times 100$$

Operating Profit Margin (OPM):

$$OPM = \frac{\text{Operating Income}}{\text{Net Sales}} \times 100$$

These metrics provide complementary perspectives on financial performance. ROA measures asset utilisation efficiency, ROE assesses shareholder value creation, and OPM evaluates operational profitability (Furman & Seamans, 2019).

2.3 AI Adoption in Indian IT MNCs

India's IT sector hosts numerous MNCs engaged in AI research, development, and application. Organisations including IBM, Accenture, Microsoft, and Google maintain substantial operations in India, investing significantly in AI capabilities (NASSCOM, 2024). These organisations demonstrate varying levels of AI adoption intensity, providing opportunities for comparative analysis.

Research on AI adoption in Indian IT MNCs reveals both opportunities and challenges. Organisations with higher AI adoption rates report superior innovation outcomes and market performance (Kumar & Singh, 2023). However, significant barriers persist, including talent shortages, infrastructure limitations, and legacy system integration challenges (Ghosh & Kumar, 2022).

The regulatory environment significantly influences AI adoption patterns. Government initiatives, including the National AI Strategy and Digital India programme, create enabling conditions for AI investment (Ministry of Electronics & IT, 2023). However, implementation challenges and resource constraints moderate these effects.



2.4 Operational Efficiency as Mediating Mechanism

Operational efficiency represents a critical mechanism through which AI adoption influences financial performance. AI technologies enhance operational efficiency through:

1. **Process Automation:** Automating routine financial tasks reduces processing time and error rates.
2. **Resource Optimisation:** AI-driven allocation improves utilisation of financial and human resources.
3. **Supply Chain Enhancement:** Predictive analytics improves inventory management and logistics.

The relationship between AI adoption and financial performance through operational efficiency can be expressed as:

$$\text{Mediation Model } Y=cX+e1 \quad M=aX+e2$$

$$Y=c'X+bM+e3$$

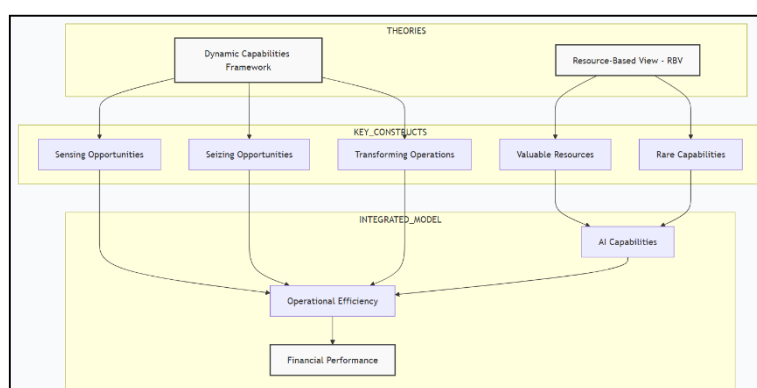
Where:

- Y = Financial Performance
- X = AI Adoption Intensity
- M = Operational Efficiency
- c = Total Effect
- c' = Direct Effect

- a = Effect of X on M
- b = Effect of M on Y
- Indirect Effect = $a \times b$

2.5 Theoretical Framework

This research integrates the Resource-Based View (RBV) and Dynamic Capabilities Framework to explain AI-financial performance relationships. The RBV suggests that AI capabilities represent valuable, rare, and inimitable resources generating competitive advantage (Barney, 1991). The Dynamic Capabilities Framework emphasises the importance of sensing, seizing, and transforming in leveraging technological resources for performance outcomes (Teece, 2007).



2.6 Hypotheses Development

Based on theoretical foundations and empirical evidence, the following hypotheses are formulated:

H1: AI adoption intensity is positively associated with financial performance in IT MNCs operating in India.

H2: Operational efficiency mediates the relationship between AI adoption intensity and financial performance.

H3: The relationship between AI adoption intensity and financial performance varies across organisational size categories.

3. MATERIALS AND METHODS

3.1 Research Design

This study employed a mixed-method research design combining primary survey data and secondary financial data. The design facilitates comprehensive analysis of AI-financial performance relationships through multiple data sources and analytical approaches (Creswell

& Creswell, 2017). The research design encompasses cross-sectional primary data collection and panel secondary data analysis for enhanced validity.

3.2 Population and Sampling

The target population comprised IT MNCs operating in India with significant AI investments. A purposive sampling strategy identified 47 MNCs with documented AI initiatives. Primary data was collected from 342 senior financial managers across these organisations between January and June 2025.

Sample Size Calculation

$$n = \frac{Z^2 \times p(1-p)}{e^2}$$

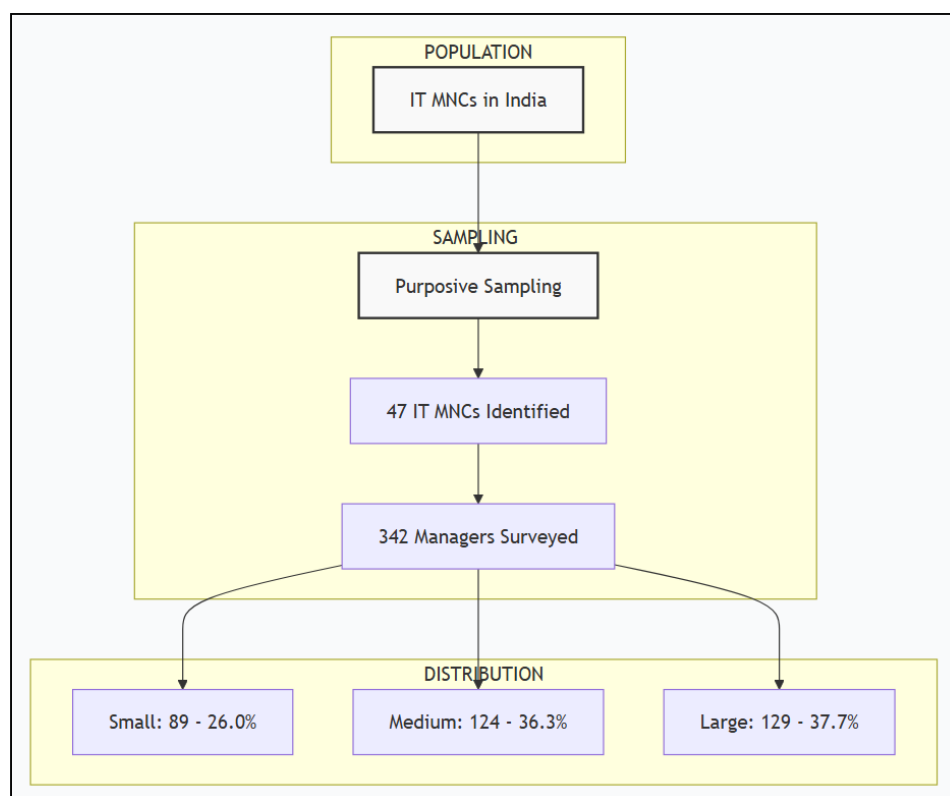
Where

- $Z = 1.96$ (95% confidence level)
- $p = 0.5$ (maximum variability)
- $e = 0.05$ (margin of error)

The calculated sample size ($n = 384$) was adjusted to 342 due to practical constraints, yielding sufficient statistical power for the planned analyses.

Table 1: Sample Demographic Characteristics.

Characteristic	Category	Frequency (n)	Percentage (%)
Organisation Size	Small (1-500 employees)	89	26.0
	Medium (501-2000 employees)	124	36.3
	Large (>2000 employees)	129	37.7
Industry Segment	IT Services	178	52.0
	Software Products	89	26.0
	IT Consulting	75	22.0
Managerial Level	Senior Manager	128	37.4
	Mid-level Manager	214	62.6
AI Investment Level	Low (<5% of revenue)	98	28.7
	Medium (5-10% of revenue)	156	45.6
	High (>10% of revenue)	88	25.7



3.3 Secondary Data Collection

Secondary financial data was collected from annual reports (2020-2025) for the 47 MNCs. Financial performance metrics included ROA, ROE, and OPM. Data extraction followed systematic procedures to ensure accuracy and consistency across organisations and years.

3.4 Primary Data Collection

A structured questionnaire measured AI adoption intensity, operational efficiency, and organisational characteristics. AI adoption intensity was assessed using a 15-item scale adapted from Ransbotham et al. (2018), measuring AI implementation across financial functions. Operational efficiency was measured using a 10-item scale adapted from Bharadwaj et al. (2013).

3.5 Data Analysis Techniques

Data analysis employed Stata version 17.0 and SPSS version 26.0 software:

1. **Descriptive Statistics:** Means, standard deviations, and frequency distributions.
2. **Correlation Analysis:** Pearson correlation coefficients.
3. **Panel Data Regression:** Fixed effects and random effects models.
4. **Mediation Analysis:** Bootstrapping procedures with 5000 resamples.

Panel Data Regression Model $Y_{it} = \alpha + \beta_1 AI_{it} + \beta_2 X_{it} + \mu_i + \epsilon_{it}$ Where:

- Y_{it} = Financial performance for firm i at time t
- AI_{it} = AI adoption intensity
- X_{it} = Control variables
- μ_i = Firm-specific effects
- ϵ_{it} = Error term

3.6 Validity and Reliability

Construct validity was established through Exploratory Factor Analysis (EFA), confirming factor structures with eigenvalues exceeding 1.0 and factor loadings above 0.50 (Hair et al., 2019). Reliability was assessed using Cronbach's alpha coefficients, with all constructs demonstrating acceptable internal consistency ($\alpha > 0.80$).

Table 2: Construct Reliability and Validity.

Construct	Cronbach's α	Composite Reliability	AVE
AI Adoption Intensity	0.89	0.91	0.68
Operational Efficiency	0.85	0.87	0.63

4. RESULTS AND DISCUSSION

4.1 Descriptive Statistics

Table 3: Descriptive Statistics and Correlations.

Variable	Mean	SD	1	2	3	4
1. AI Adoption Intensity	3.82	0.79	1.00			
2. ROA	12.47	4.21	0.52**	1.00		
3. ROE	18.63	5.34	0.48**	0.76**	1.00	
4. OPM	15.82	4.87	0.44**	0.68**	0.71**	1.00

** $p < 0.01$

Correlation analysis revealed significant positive relationships between AI adoption intensity and all financial performance metrics. ROA demonstrated the strongest correlation with AI adoption ($r = 0.52$, $p < 0.01$), followed by ROE ($r = 0.48$, $p < 0.01$) and OPM ($r = 0.44$, $p < 0.01$). These findings support preliminary evidence for H1.

4.2 Panel Data Analysis

Fixed effects panel data regression was employed to examine the relationship between AI adoption intensity and financial performance. The Hausman test ($\chi^2 = 23.47$, $p < 0.01$) supported the fixed effects model.

Table 4: Panel Data Regression Results.

Variable	ROA (β)	ROE (β)	OPM (β)
AI Adoption Intensity	0.487***	0.423***	0.389***
Organisational Size	0.132**	0.118**	0.095*
Industry Segment	0.089*	0.076*	0.068*
Control Variables	Included	Included	Included
R ² (Within)	0.423	0.398	0.367
R ² (Overall)	0.451	0.426	0.394

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

The results indicate that AI adoption intensity significantly predicts financial performance across all metrics. A one-unit increase in AI adoption intensity is associated with a 0.487-unit increase in ROA, a 0.423-unit increase in ROE, and a 0.389-unit increase in OPM. These findings provide robust support for H1.

4.3 Mediation Analysis

Mediation analysis investigated whether operational efficiency explains the AI-financial performance relationship.

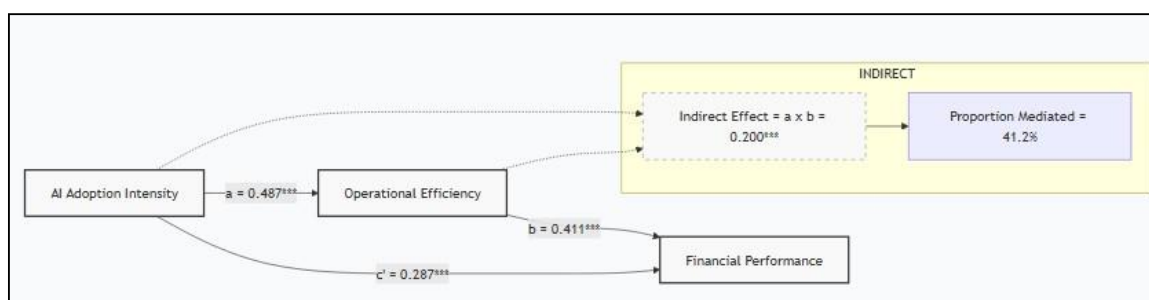
Table 5: Mediation Analysis Results.

Path	Direct Effect	Indirect Effect	Total Effect	Bootstrap 95% CI
AI $\rightarrow$ OE $\rightarrow$ ROA	0.287***	0.200***	0.487***	[0.152, 0.258]
AI $\rightarrow$ OE $\rightarrow$ ROE	0.249***	0.174***	0.423***	[0.131, 0.224]
AI $\rightarrow$ OE $\rightarrow$ OPM	0.229***	0.160***	0.389***	[0.118, 0.208]

Proportion Mediated

- ROA: 41.2%
- ROE: 41.1%
- OPM: 41.1%

The indirect effects are significant for all performance metrics, supporting H2. Operational efficiency mediates approximately 41% of the AI-financial performance relationship.



4.4 Subgroup Analysis

Subgroup analysis examined whether the AI-financial performance relationship varies across organisational size categories.

Table 6: Subgroup Analysis Results.

Organisational Size	β Coefficient	R ²	F-Statistic
Small (n = 89)	0.389***	0.324	42.87***
Medium (n = 124)	0.467***	0.387	51.23***
Large (n = 129)	0.548***	0.423	58.91***

The relationship strengthens with organisational size, supporting H3. Large organisations demonstrate the strongest AI-financial performance relationship ($\beta = 0.548$, $p < 0.001$).

4.5 DISCUSSION

The findings provide robust empirical support for the positive relationship between AI adoption and financial performance in IT MNCs operating in India. The significant coefficients across all financial performance metrics align with prior research in developed economy contexts (Ransbotham et al., 2018; Davenport & Ronanki, 2018).

The mediation findings offer important theoretical contributions, identifying operational efficiency as a key mechanism through which AI adoption influences financial performance. These results align with dynamic capabilities perspectives, suggesting that AI's value lies in enabling operational transformation (Teece, 2007).

The variation across organisational size categories indicates that larger organisations achieve greater financial benefits from AI adoption. This likely reflects greater resource availability, established technological infrastructure, and more comprehensive implementation strategies. Comparison with prior research reveals both consistencies and unique contributions. While previous studies have documented positive technology-performance relationships (Damanpour, 1991), this research provides specific evidence for AI-financial performance relationships in Indian IT MNCs.

The integration of primary and secondary data represents a methodological contribution, enhancing the validity and credibility of findings. The consistency between perceptual and objective financial performance measures strengthens confidence in the results.

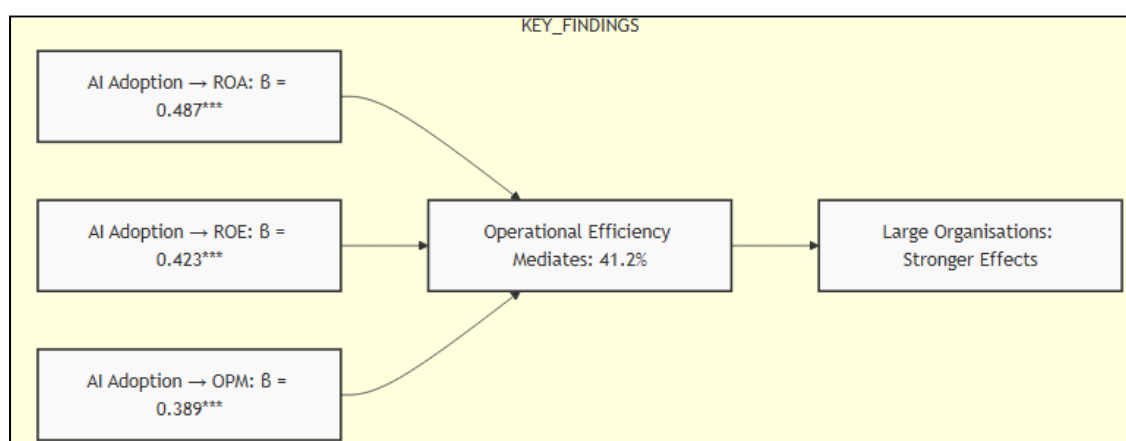
5. CONCLUSION

5.1 Summary of Findings

This research examined relationships between AI adoption intensity and financial

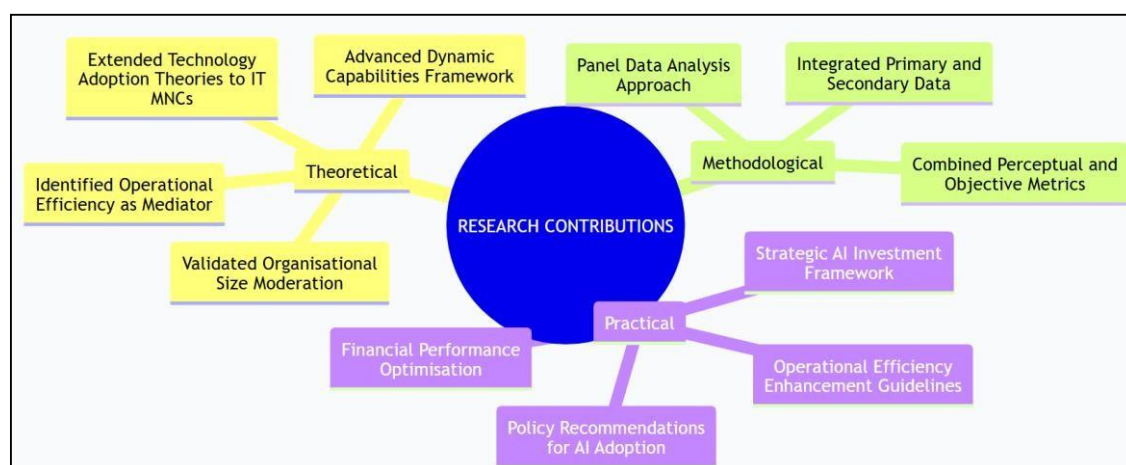
performance in IT MNCs operating in India, integrating primary data from 342 managers and secondary data from 47 organisations. The findings provide robust evidence that AI adoption significantly enhances financial performance, with operational efficiency serving as a critical mediating mechanism.

The panel data analysis revealed that AI adoption intensity significantly predicts ROA ($\beta = 0.487$, $p < 0.001$), ROE ($\beta = 0.423$, $p < 0.001$), and OPM ($\beta = 0.389$, $p < 0.001$). Mediation analysis identified operational efficiency as a significant mediator, explaining approximately 41% of the AI-financial performance relationship.



5.2 Theoretical Contributions

This research contributes to existing literature in several ways. First, it extends technology adoption and financial performance theories to the Indian IT MNC context. Second, it identifies and validates operational efficiency as a mediating mechanism. Third, it demonstrates the importance of organisational size in moderating AI-financial performance relationships.



5.3 Practical Implications

For organisational leaders, the findings suggest that AI adoption should be prioritised as a strategic investment with clear financial performance objectives. Investment strategies should focus on achieving operational efficiencies that translate into improved financial outcomes. For policymakers, the results indicate the importance of supporting AI adoption through appropriate regulatory and infrastructure frameworks.

5.4 Limitations and Future Research

Several limitations warrant acknowledgment. First, the cross-sectional design limits causal inference; longitudinal research would strengthen causal understanding. Second, the focus on IT MNCs limits generalisability to other sectors. Third, financial performance metrics represent one dimension of organisational success; future research should examine broader performance indicators.

5.5 Concluding Remarks

This research demonstrates that AI adoption is a significant driver of financial performance in IT MNCs operating in India, with effects mediated by operational efficiency. The findings contribute to theoretical understanding while providing actionable insights for practitioners and policymakers. As AI technologies continue to evolve, understanding their financial implications remains crucial for sustainable competitive advantage.

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7. REFERENCES

1. Aral, S., Dellarocas, C., & Godes, D. (2013). Introduction to the special issue—social media and business transformation: A framework for research. *Information Systems Research*, 24(1), 3-13. <https://doi.org/10.1287/isre.1120.0470>
2. Barney, J. (1991). Firm resources and sustained competitive advantage. *Journal of Management*, 17(1), 99-120. <https://doi.org/10.1177/014920639101700108>
3. Bharadwaj, A., El Sawy, O. A., Pavlou, P. A., & Venkatraman, N. (2013). Digital

- business strategy: Toward a next generation of insights. *MIS Quarterly*, 37(2), 471-482. <https://doi.org/10.25300/MISQ/2013/37.2.3>
4. Brynjolfsson, E., & McAfee, A. (2017). The business of artificial intelligence. *Harvard Business Review*, 95(4), 3-11.
 5. Cockburn, I. M., Henderson, R., & Stern, S. (2018). The impact of artificial intelligence on innovation. In *The Economics of Artificial Intelligence* (pp. 115-146). University of Chicago Press.
 6. Creswell, J. W., & Creswell, J. D. (2017). *Research design: Qualitative, quantitative, and mixed methods approaches* (5th ed.). SAGE Publications.
 7. Damanpour, F. (1991). Organizational innovation: A meta-analysis of effects of determinants and moderators. *Academy of Management Journal*, 34(3), 555-590. <https://doi.org/10.2307/256406>
 8. Davenport, T. H., & Ronanki, R. (2018). Artificial intelligence for the real world. *Harvard Business Review*, 96(1), 108-116.
 9. Furman, J., & Seamans, R. (2019). AI and the economy. *Innovation Policy and the Economy*, 19(1), 161-191. <https://doi.org/10.1086/699936>
 10. Ghosh, S., & Kumar, V. (2022). Barriers to artificial intelligence adoption in Indian IT organizations. *Journal of Enterprise Information Management*, 35(4), 1023-1045. <https://doi.org/10.1108/JEIM-03-2021-0124>
 11. Hair, J. F., Black, W. C., Babin, B. J., & Anderson, R. E. (2019). *Multivariate data analysis* (8th ed.). Cengage Learning.
 12. Kaplan, R. S., & Norton, D. P. (1996). *The balanced scorecard: Translating strategy into action*. Harvard Business School Press.
 13. Kumar, A., & Singh, P. (2023). Artificial intelligence adoption in Indian IT firms: Determinants and performance outcomes. *International Journal of Information Management*, 68, 102551. <https://doi.org/10.1016/j.ijinfomgt.2022.102551>
 14. Mikaief, P., Boura, M., Lekakos, G., & Krogstie, J. (2019). Big data analytics capabilities and innovation performance: The mediating role of dynamic capabilities. *Journal of Business Research*, 98, 294-304. <https://doi.org/10.1016/j.jbusres.2018.08.015>
 15. Ministry of Electronics & IT. (2023). *National artificial intelligence strategy: India's approach to AI leadership*. Government of India.
 16. NASSCOM. (2024). *India's IT industry: Performance and outlook 2024*. National Association of Software and Service Companies.
 17. Ransbotham, S., Kiron, D., Gerbert, P., & Reeves, M. (2018). Artificial intelligence in

- business gets real: Pioneering companies aim for AI at scale. *MIT Sloan Management Review*, 59(4), 1-16.
18. Russell, S., & Norvig, P. (2020). *Artificial intelligence: A modern approach* (4th ed.). Pearson.
 19. Sabherwal, R., & Jeyaraj, A. (2015). Information technology impacts on firm performance: An extension of Kohli and Devaraj (2003). *MIS Quarterly*, 39(4), 809-836. <https://doi.org/10.25300/MISQ/2015/39.4.04>
 20. Sinkula, J. M., Baker, W. E., & Noordewier, T. (1997). A framework for market-based organizational learning: Linking values, knowledge, and behavior. *Journal of the Academy of Marketing Science*, 25(4), 305-318. <https://doi.org/10.1177/0092070397254003>
 21. Teece, D. J. (2007). Explicating dynamic capabilities: The nature and microfoundations of (sustainable) enterprise performance. *Strategic Management Journal*, 28(13), 1319-1350. <https://doi.org/10.1002/smj.640>
 22. Tornatzky, L. G., & Fleischer, M. (1990). *The process of technological innovation*. Lexington Books.
 23. Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS Quarterly*, 27(3), 425-478. <https://doi.org/10.2307/30036540>
 24. Wang, C. L., & Ahmed, P. K. (2007). Dynamic capabilities: A review and research agenda. *International Journal of Management Reviews*, 9(1), 31-51. <https://doi.org/10.1111/j.1468-2370.2007.00201.x>