Evaluating AI Disclosures in Indian IT-Services Firms: A Multiyear Study of Productivity Outcomes

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Abstract

Indian IT-services companies have increasingly begun to emphasize terms related to AI, automation, and digital engineering in their annual reports. This shift appears to be part of a broader effort to position themselves as technologically forward. The present study looks at whether this growing attention to AI in corporate communication actually corresponds with measurable changes in productivity. Using data from ten major IT- services firms covering FY2021 to FY2025, the analysis combines text-derived indicators such as how often AI-related themes occur in annual reports and the breadth of initiatives mentioned with operational measures like revenue per employee and the gap between revenue and headcount growth. In order to determine whether earlier AI-focused communication has any bearing on performance two years later, a delayed-effect lens is used. There is a discernible increase in the frequency with which businesses discuss AI after FY2023, although efficiency gains are not as consistent throughout the group. Some companies seem to exhibit consistency between their performance and their report highlights while others talk a lot about AI, without affecting their efficiency metrics. Elements such as how deeply digital services contribute to revenue and the maturity of AI-related programs seem to matter more than the volume of the disclosures alone.

Keywords- Education, Computer Graphics, Visual Depiction, Virtual Reality, Animation, Visual Effects

1. Introduction

AI has become standard language in how Indian IT-services firms describe themselves. Annual reports now spend considerable space on AI, automation, cloud engineering, and analytics, typically framed as evidence of technical sophistication. What is less clear is whether more AI language in these reports actually corresponds to better operating efficiency.

Work on corporate disclosure has shown that how companies communicate often shapes expectations among investors and clients, regardless of the firm's actual readiness to deliver. Studies on AI adoption consistently find that productivity gains tend to show up only after supporting systems, processes, and talent have evolved alongside the technology. This creates an obvious question for Indian IT services, a sector where performance depends heavily on workforce leverage and the ability to commercialise digital capabilities.

This study applies a two-year lag model to ask whether AI signalling in earlier years corresponds to efficiency improvements later. The aim is to distinguish firms that convert AI rhetoric into measurable performance gains from those where the narrative emphasis does not translate into operational results.

Objectives:

- Measure AI-disclosure intensity in Indian IT-services firms.
- Assess execution maturity through initiative count and digital-revenue share.
- Assess productivity outcomes based on revenue per employee and efficiency gap.
- Test for a two-year lag between AI signalling and performance.
- Classify firms by disclosure intensity and productivity to distinguish executors from signallers.

2. Related Work

1. AI Adoption and Productivity
Research on AI and productivity is consistent on one point: outcomes depend on organisational readiness, not just adoption. Brynjolfsson and McElheran [3] find that algorithmic decision tools produce performance gains only when firms have strong data foundations in place. Aghion, Jones, and Jones [2] argue that AI-enabled growth requires alignment with existing innovation capacity. Tambe, Hitt, and Brynjolfsson [10] observe that efficiency improvements in AI-intensive firms take time to materialise. Choudhury et al. [11] point to task restructuring as a precondition for realising AI's value. OECD [16] and Naqbi et al. [17] document that AI's effect on efficiency varies considerably across industries.

2. Narrative Disclosure and Strategic Signalling
Li [1] shows that forward-looking language in corporate filings influences investor sentiment even under uncertainty. Investor presentations work similarly. Feng, Zhang, and McVay [4] find that disclosure tone is actively managed to frame performance. Loughran and McDonald [8] offer tools for quantifying disclosure intensity. Taken together, these studies suggest that AI language in annual reports carries a signalling function, which is exactly what this study tests.

3. Digital Transformation Capabilities
Digital maturity is a stronger predictor of firm performance than how much a company talks about transformation. Gartner and Iansiti [12] find that transformation creates value only when leadership, processes, and technology move together. Ransbotham et al. [13] show that structured AI programs consistently outperform ad hoc ones. Ghosh and Mukherjee [14], studying Indian IT firms specifically, find that the depth of digital capability drives results more than narrative emphasis. Execution quality is what determines whether AI adoption produces measurable gains.

4. Lag Effects in Technology Impact
Technology-driven productivity gains usually appear only after complementary practices develop. Aral, Brynjolfsson, and Van Alstyne [7] show that IT returns materialise after workflow changes have taken hold. NBER studies [10][11] document similar lags in AI outcomes, and Rock [15] connects results to gradual skill accumulation. These findings provide the rationale for the two-year lag window used here.

5. Research Gap
Prior work has established the conditions under which AI improves productivity and has examined how disclosure language shapes perception. What is missing is a study that asks whether AI disclosures by Indian IT-services firms predict future productivity outcomes, or how digital maturity and initiative depth shape that relationship. This study addresses that gap through a combined text-analysis and financial-performance approach.

3. Materials and Methods

1. Dataset

The study uses panel data from 10 major Indian IT services firms observed from FY2021 to FY2025, producing 50 firm-year observations. Annual reports and financial disclosures are the primary data sources.

2. Variable Extraction
- AI Disclosure Intensity: the normalized frequency of AI-related keywords in annual reports.
- Digital Revenue %: the share of income from cloud, data, analytics, and AI-related services.
- Initiative Count: explicitly mentioned AI platforms, solutions, or Centres of Excellence (CoEs).
- Productivity outcomes: measured through Revenue per Employee and the Efficiency Gap, which is the difference between revenue growth and headcount growth.
- An M&A flag identifies years affected by mergers or acquisitions to reduce distortions in causal interpretation.

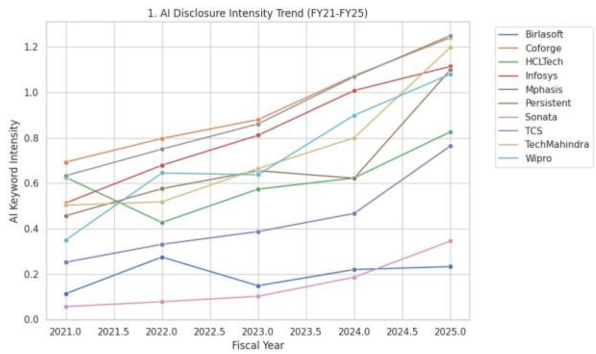
3. Analytical Model

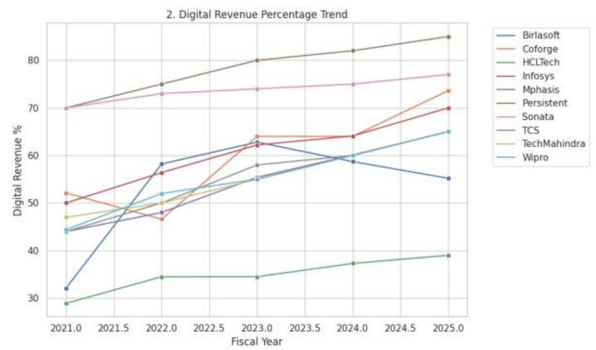
A two-year lag model tests whether AI disclosure at year T-2 predicts the efficiency gap at year T. The analysis uses descriptive trends, cross-sectional metrics, and lagged scatter plots. M&A years are flagged to prevent bias.

Variable	Mean	Median	Std. Dev.	Min	Max
Operating Margin (%)	17.37	17.8	4.74	6.7	26.8
Efficiency Gap	4.96	5.62	10.93	-43.7	29.7
Revenue per Employee (Cr)	0.464	0.38	0.259	0.286	1.504
Digital Revenue (%)	58.16	59.35	13.46	28.9	85
Initiative Count	17.7	16	9.08	4	45
Keyword Intensity	0.622	0.63	0.328	0.057	1.25

Summary Statistics

The dataset shows considerable spread in how often firms discuss AI, reflecting different communication strategies. Digital revenue shares vary widely, reflecting unequal progress in shifting toward modern service lines. The efficiency gap moves in both directions across years, confirming that a lag-based approach is appropriate. 22. Efficiency Results AI disclosure intensity has risen across most firms, particularly after FY2023. This points to a sector wide move toward positioning AI as a core differentiator. Whether the amplified narrative corresponds to real commercial progress is a separate question, one that requires comparing disclosure trends against composition.





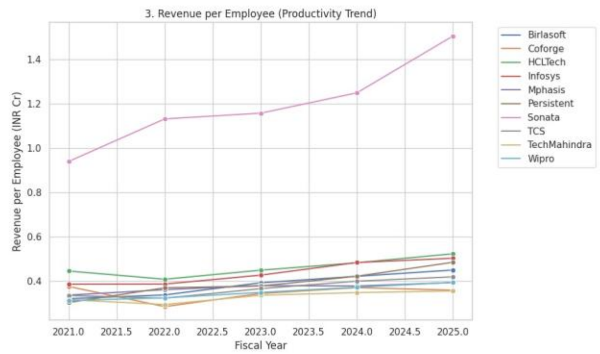
4. Results and Discussion

1. Productivity Patterns

Revenues generated per employee are experiencing consistent improvement across several firms, notably TCS, Infosys, and Persistent, indicating enhanced talent utilization and increased leverage of digital service capabilities. Organizations that persistently elevate productivity tend to demonstrate superior alignment between their AI initiatives and operational efficiency, suggesting that modernization efforts are successfully translating into measurable output gains. Conversely, other companies, such as Wipro and Tech Mahindra, exhibit more stable or fluctuating patterns, reflecting challenges in uniform execution or a continued reliance on headcount driven growth models.

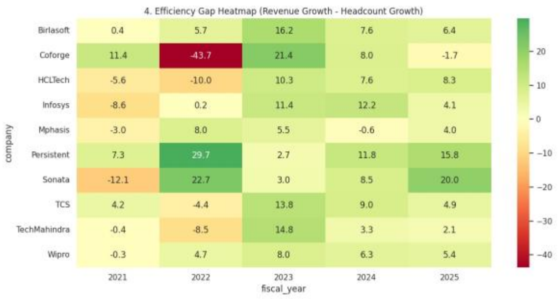
2. Efficiency Results

The efficiency gap varies considerably. TCS, Infosys, Persistent, and Coforge have posted positive gaps across multiple years, where revenue growth ran ahead of headcount growth, indicating effective scaling. Coforge shows an extreme negative gap of-43.7% in one year, but this reflects unusual headcount expansion tied to M&A activity, not operational deterioration. Firms with recurring negative gaps suggest structural problems: rising costs, weak demand, or returns on digital investment that have not come through. Across the group, the heatmap reveals a clear divergence. High AI disclosure and strong productivity do not consistently go together.

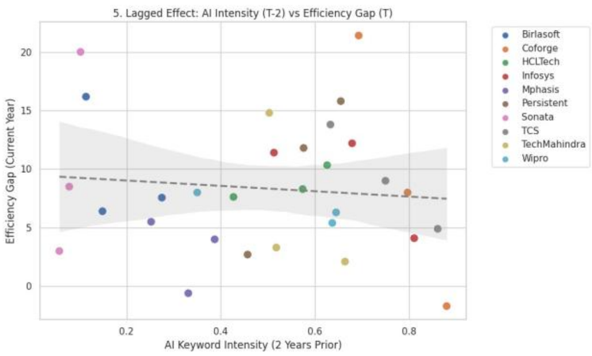


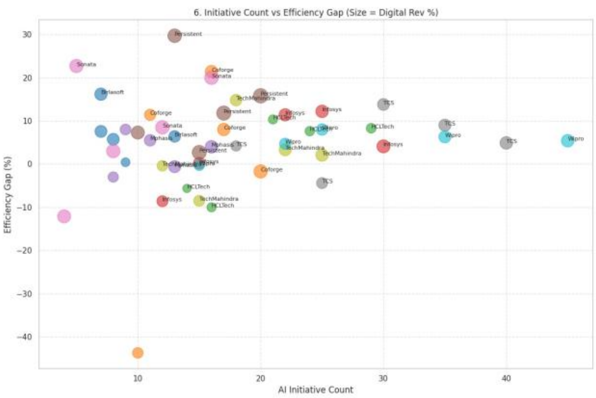
3. Lagged Effect Analysis

The lag model asks a focused question: does what firms say about AI two years earlier predict their productivity today? TCS and Infosys cluster in the positive zone of the scatter plot, suggesting their earlier narrative emphasis did correspond with later efficiency gains, consistent with a higher level of execution maturity. Firms with high disclosure but weak or negative efficiency gaps fall in the lower region, indicating that communication and operational impact came apart.



The bubble chart makes the same point differently: firms with many initiatives and strong efficiency outcomes sit in the upper-right quadrant, while those with fewer initiatives show lower and less consistent productivity. Initiative maturity, not disclosure volume, is what converts AI focus into economic results.





4. Discussion of Findings

There is a real disconnect in the data. Most firms talk extensively about AI adoption; very few consistently translate that into measurable productivity gains. Declaring an AI strategy does not confirm the organisational capacity to execute it. The firms that do show consistent efficiency gains tend to have expanded digital revenue over time, reflecting commercial progress in modern service lines rather than just narrative progress. That conclusion was complicated by M&A activity in several firm-years, where financial figures were distorted in ways that are hard to fully isolate.

	Low Productivity (Avg Efficiency Gap < 6.35)	**High Productivity (Avg Efficiency Gap ≥ 6.35)**
High Disclosure (Avg Intensity ≥ 0.709)	Signalers without Execution: Infosys, TCS	True Executors: Coforge, TechMahindra
Low Disclosure (Avg Intensity < 0.709)	Low Maturity Firms: Mphasis, Sonata	Quiet Efficient Firms: Birlasoft, Persistent

Execution vs. Signaling Matrix

5. Limitations

The analysis has several limitations worth stating clearly. The FY2021 to FY2025 window is short relative to the typical cycles of AI adoption, so some effects may not yet be visible. M&A activity complicated causal interpretation in several firmyears. Separating genuine operational changes from structural headcount shifts was difficult. Annual reports also use inconsistent language to define digital revenue, making cross-firm comparisons imprecise. The two-year lag is a useful simplification, but actual implementation speeds vary across firms and contexts.

5. Conclusion

Major Indian IT-services firms are disclosing more about AI, but productivity improvements remain uneven. TCS, Infosys, Persistent, and Coforge show a real relationship between positive efficiency gaps, digital revenue growth, and AI program activity. Others report extensively about AI without the corresponding performance. Signalling alone does not drive operational improvement. What matters more is execution depth, initiative maturity, and whether firms have genuinely built out digital capabilities alongside the rhetoric.

Future work can apply semantic NLP methods to assess the quality and intent of disclosures beyond keyword counts. Extending the timeframe would strengthen lag-based evaluations. Detailed deal-level data would help isolate structural headcount changes driven by M&A. Expanding the sample to mid- and lower-tier IT firms would give a fuller picture of how digital maturity and investment levels shape AI adoption outcomes across the broader industry.

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