Journal of Applied Economic Sciences
Volume XXI, Summer, Issue 3(93), 2026

From Digitization to Intelligence: Assessing the Impact of AI Maturity on Financial Resilience and Market Value in Indian Public Sector Enterprises

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Article's History
Received 29th of April, 2026; *Revised* 9th of June, 2026; *Accepted* 21st of June, 2026; *Available online*: 30th of June, 2026. *Published* as research article in the Volume XXI, Summer 3(93), 2026.

Suggested Citation
Yelamanchili, R. K. (2026). From Digitization to Intelligence: Assessing the Impact of AI Maturity on Financial Resilience and Market Value in Indian Public Sector Enterprises. *Journal of Applied Economic Sciences*, Volume XXI, Summer, 3(93), 917–934. https://doi.org/10.57017/jaes.v21.3(93).12

Abstract

Artificial intelligence (AI) is increasingly reshaping corporate strategy and organizational performance, yet empirical evidence on its impact in large public sector enterprises remains limited. This study examines the relationship between AI maturity, financial resilience, and market value among Indian Maharatna companies, which represent strategically important enterprises operating in infrastructure, energy, defence, and service sectors.

A novel AI Maturity Index (AIMI) was developed using a local large language model (LLM) to analyse approximately 50,000 pages extracted from 140 annual reports covering the period 2016–2025. The AI-generated maturity scores were validated through a retrieval-augmented generation (RAG) framework and human expert verification. Financial data obtained from CMIE ProwessIQ were used to estimate financial resilience, market value, human capital productivity, and operational efficiency using fixed-effects panel regression models controlling for firm size, leverage, and profitability. The results reveal a significant structural break around 2020 and a marked increase in AI maturity following 2021, indicating a transition from basic digitalization to cognitive AI adoption. Higher AI maturity is found to significantly improve financial resilience and market value, while also contributing to operational and human capital performance.

The findings suggest that although Maharatna enterprises have made substantial progress in adopting cognitive AI, the economic benefits of these investments emerge gradually and require time to be fully reflected in corporate performance and market valuation. The study contributes a novel AI maturity measurement framework and provides practical insights for policymakers and managers seeking to maximize the strategic value of AI investments.

Keywords: artificial intelligence; AI maturity; financial resilience; Altman Z-Score; Tobin's Q; textual forensics; public sector economics; digital transformation.

JEL Classification: D22; O14; G30; O33; L32.

Introduction

Globally, artificial intelligence is redefining the way businesses are run and helping organizations to optimize costs, enhance profitability, and create value to shareholders. Private sector enterprises are the frontrunners in adopting AI technologies. Public sector enterprises are assumed to be slow adopters due to their size, structure, and administration. Presently, much of the research on AI adoption is focused on private sector. There is limited research on AI adoption and AI maturity in the context of Indian Central Public Sector Enterprises (CPSEs), especially Indian Maharatnas which have lot of autonomy in running their business and which acts as benchmark of national economy. These Maharatnas manage critical infrastructure and national importance sectors like defence, heavy industries, oil-gas, mines-minerals, power, and service. It is particularly important to know whether Maharatnas are adopting AI or not, at what level they are adopting it, and what is the impact of AI adoption on their productivity. Answers to these questions will be of significant help to other central and state public sector enterprises and to the Nation.

AI adoption and increased organizational productivity has two facets. On one side there is convincing evidence in support of dynamic capabilities theory where, AI enhances organizational creativity and performance (Almheiri et al., 2024). Similarly, AI improves organizational productivity through data driven decision making, enhances customer sentiment, increases employee retention and lead to faster learning (Brynjolfsson et al., 2023). On the second side there exists support for modern productivity paradox (Solow, 1987) where, increased AI investments may not always translate into immediate productivity gains (Khalil et al., 2025).

Another important aspect of AI adoption studies is measurement metric. Traditional works used survey based, patent based, simple dictionary based or bag of words metrics to measure AI adoption which fails to uncover AI washing. To overcome this challenge few authors applied text-based analysis using annual reports (Haapamäki & Sihvonen, 2026; Hoberg & Phillips, 2016). Recent advancement is the forensic textual analysis of long documents (Michelet & Breitinger, 2024; Studiawan et al., 2025).

In this paper, using forensic textual analysis we develop the AI Maturity Index (AIMI). Applying this novel methodology, we generate AI maturity score for each of the Maharatnas for 10-year period from 2016 to 2025. We employ a local large language model (Meta Llama 3.2) to churn approximately 50,000 pages of 140 annual reports. Once the Llama generated scores, we triangulated the results with two other methods (human in the loop and retrieval augmented generative model (RAG)), where we manually verified 10% of annual reports randomly and another forensic textual analysis is run using investor presentations with RAG model. We find consistency among all the three methods. In our econometric models we use this robust AI Maturity Index and financial data sourced from ProwessIQ to measure the impact of AI maturity on financial resilience, market value, human capital, and operational efficiency.

This paper makes three unique contributions to the existing body of knowledge. First, methodologically, this work pioneers by fusing local large language model-based forensics with human in the loop and RAG methods. This triangulation extracts the best information from lengthy annual reports and minimises noise. Second, this paper reports a notable change in the Maharatnas digital initiatives, there is dramatic shift from digitization to cognitive AI over the study period. Furthermore, there is a statistically significant impact of AI Maturity on financial resilience and market value. Finally, the study provides empirical evidence for dynamic capabilities theory, modern productivity paradox, and resource orchestration theory.

The remainder of the paper is presented as follows: literature review is presented in Section 1, methodology is presented section 2, empirical results are discussed in Section 3. Section 4 discusses the findings, Section 5 makes recommendations, and last section concludes the paper.

1. Literature Review

The Resource Based Value framework (Barney, 1991) proposes that organizations derive competitive advantage through their valuable, rare, inimitable, and non-substitutable economic resources and increases it with information processing and decision making. Relatedly, the Dynamic Capabilities framework (Teece et al., 1997) posits that in the age of rapid technological advancements organizations need to hone their internal technologies, organizational, and managerial capabilities to have competitive advantage. Furthermore, Resource Orchestration Theory (Simon et al., 2011) suggests that organizations can realize better financial outcomes when managers leverage economic resources effectively.

Certain studies provide empirical evidence to these frameworks. For example, Vial (2019) reports that digital technologies create disruptions, forces organizations to break organizational barriers, bring structural changes to create value to their stakeholders. Mikalef & Gupta (2021) provide empirical evidence on how AI capability results in increased organizational creativity and performance.

Brynjolfsson & McElheran (2016) provide evidence for data driven decision making (DDD) and concludes that DDD enhances productivity supported by usage of information technology and firm learning. Gupta & Mehta (2024) in their systematic literature review, concludes that machine learning approaches can achieve better classification accuracy. Martens (2024) is sceptic about AI's contribution to productivity growth and explains that productivity usually catches up slowly compared to costs. Indian Maharatnas are incurring excessive costs for AI adoption and upskilling the human capital. There is a possibility that Maharatnas may encounter modern productivity paradox. In addition, Maharatnas operate in a unique environment where AI adoption is influenced by government vision and mission (DiMaggio & Powell, 1983; Cuervo-Cazurra et al., 2014).

Majority of existing research on technology and financial performance of organizations use profitability ratios or key financial indicators as response variables. Li et al. (2025) suggest that impact of technology should be assessed on financial resilience. In addition, AI technologies like predictive maintenance, risk analytics, demand forecasting will enhance firm’s market value. Altman’s (1968) Z-score and Tobin’s (1969) Q-score are considered as gold standards to measure financial resilience and market value.

An important challenge in current empirical accounting research is the measurement of AI adoption or AI maturity. Traditional studies relied on dichotomous agreement proxies (Yes/No) or simple keyword frequency (Loughran & McDonald, 2011). However, Cao et al. (2023) argue that keyword counts are prone to AI Washing and emphasize that AI adoption is an intangible capability that confirms in stages, from foundational data points to autonomous decision making and suggest use of multidimensional scale.

The period of 2021 - 2026 has been characterized as the period of cognitive intelligence. Agarwal et al. (2024) reports that AI was crucial in reorganizing businesses in the manufacturing, electronics, and services sectors after the pandemic. Song et al. (2026) further demonstrate that digital transformation in state owned enterprises reduced principal-agent costs, improved resource concordance, improved incentive effectiveness, and intellectual capital without increasing costs.

Recent empirical works have redefined the link between technology and financial health. Huang & Lin (2025) proved that AI adoption enhances financial performance and market value. They measured financial performance using few key financial ratios and market value with Tobin's Q. Chen et al. (2026) empirically proves that AI significantly enhances corporate resilience. Further adds that AI strengthens resilience through optimizing resource allocation efficiency, enhancing risk management, and driving continuous innovation. Suwanposri et. al. (2025) reports that operational efficiency, supportive governmental policies, and suitability of technology are the key drivers of technology adoption. Sichoongwe (2024) study results show that innovation of the firm and firm size has a significant impact on digital technology adoption. Riehl et al. (2025) provides empirical evidence on how textural characters that are mined from digital news of online magazines will help gain market insights and measure financial success. These studies provide empirical evidence of association between artificial intelligence and financial resilience.

Despite the AI hype, the productivity paradox (Solow, 1987) remains a concern. Brynjolfsson et al. (2024) updated their seminal work, suggesting that generative AI and ML follow a J-curve trajectory: productivity initially dips due to massive complementary investment before a sharp rise.

Most of the current research on AI adoption focuses on private firms, there is a need for longitudinal study in the context of Indian central public sector enterprises. At the same time most, studies rely on cross-sectional surveys or simple keyword counts (Loughran & McDonald, 2011), studies using panel data and AI maturity scale is sparse. Furthermore, very few studies have successfully integrated Local LLM Forensics with CMIE Prowess financial data to create a double audited dataset. Finally, while profit is the major focus, financial resilience (Z-Score), market value (Tobin's Q), human capital, and operational efficiency as a response of AI maturity remains understudied.

The review of the existing literature highlights several unresolved issues concerning the measurement of AI maturity and its organizational consequences in public sector enterprises. In response to these gaps, this study develops a set of research questions, objectives, and testable hypotheses to investigate the relationship between AI maturity and firm performance among Indian Maharatna companies.

To address the identified research gaps, the study seeks to answer the following research questions:

RQ1. Has AI maturity significantly evolved between the foundational digitalization period (2016–2020) and the cognitive AI period (2021–2025) among Indian Maharatna enterprises?

RQ2. To what extent does AI maturity influence firms' financial resilience and market valuation?

RQ3. Does AI maturity contribute to improvements in human capital productivity and operational efficiency?

In line with the research questions, the study pursues the following objectives:

O1. To develop a multidimensional AI Maturity Index (AIMI) for measuring AI adoption among Indian Maharatna enterprises.

O2. To examine the impact of AI maturity on financial resilience and market valuation.

O3. To assess the effect of AI maturity on human capital productivity and operational efficiency.

Drawing upon the theoretical framework and prior empirical evidence, the following hypotheses are proposed for empirical testing:

H1. Indian Maharatna enterprises exhibit significantly higher AI maturity during the cognitive AI period (2021–2025) than during the foundational digitalization period (2016–2020).

H2a. Lagged AI maturity has a positive and statistically significant effect on firms' financial resilience, measured by the Altman Z-Score.

H2b. Lagged AI maturity has a positive and statistically significant effect on firms' market valuation, measured by Tobin's Q.

H3a. Lagged AI maturity has a positive and statistically significant effect on human capital productivity.

H3b. Lagged AI maturity has a positive and statistically significant effect on operational efficiency.

2. Research Methodology

Resource-based view of the firm suggests that resources influence firm performance (Crook et al., 2008). Adding to this Helfat et al. (2007) and Sirmon et al. (2007) proposes that the influence just not happen by possessing the resources, but by including managerial actions, bundling resources into capabilities, and leveraging the capabilities for competitive advantage. By integrating the frameworks of Helfat et al. (2007) and Sirmon et al. (2007, 2011) proposes a new framework termed as Resource Orchestration Theory (ROT). ROT posits that firms need to build different strategies to optimize their resources and to attain competitive advantage based on firm's scope, stage of life cycle, and managerial hierarchy.

Similarly, AI Capability Framework (Mikalef & Gupta, 2021) hypothesis that AI capability is a firm's ability to combine technology, human, and intangible resources to influence performance and enhance creativity. Next, most of the existing studies measure AI adoption on a binary scale (Yes / No), which fail to capture multidimensional complexity of AI adoption. To address these issues, we built research methodology of this paper based on ROT and the AI Capability Framework (Mikalef & Gupta, 2021). We construct a multidimensional AI Maturity Index (AIMI) to quantify the AI adoption and transition from foundational digitization to cognitive AI. We employ a longitudinal panel data design to measure the AI maturity and its impact on financial resilience, market value, human capital, and operational efficiency of India's 14 Maharatna CPSEs (Table 1) from 2016-2025.

Our 5-point AI Maturity Index is scientifically superior to binary scale because it captures the technological investments, AI applications for performance improvement, human involvement, and present and future strategies of AI adoption. Our local LLM based textual forensics model moves beyond machine listening to machine reasoning and allows us to distinguish between Maharatnas that mention AI adoption and Maharatnas that orchestrate AI for resilience and market value.

Table 1: List of Maharatnas

No	Maharatna	No	Maharatna
1	Bharat Heavy Electricals Ltd.	8	N T P C Ltd.
2	Bharat Petroleum Corpn. Ltd.	9	Oil & Natural Gas Corpn. Ltd.
3	Coal India Ltd.	10	Oil India Ltd.
4	G A I L (India) Ltd.	11	Power Finance Corpn. Ltd.
5	Hindustan Aeronautics Ltd.	12	Power Grid Corpn. Of India Ltd.
6	Hindustan Petroleum Corpn. Ltd.	13	R E C Ltd.
7	Indian Oil Corpn. Ltd.	14	Steel Authority of India Ltd.

Note: The sample comprises the 14 Indian Maharatna Central Public Sector Enterprises (CPSEs) included in the longitudinal analysis for the period 2016–2025.

Source: Authors' compilation based on the Government of India, Department of Public Enterprises.

The AI Maturity Model

The logic behind our multidimensional AI Maturity Index, rather than a simple bag of words and binary scale is rooted in the information asymmetry and impression management inherent in annual reports, investor presentation, and news statements by corporates. Cao et al. (2023) notes that corporates often engage in AI washing, where technological talk exceeds actual operational actions. Furthermore, Vial (2019) proposes a digital transformation framework where positive and negative outcomes of digital technologies follow a process from introduction, execution, response, and outcomes. Our 5-point textual forensic scale captures these frameworks.

Our 5-point multidimensional AI Maturity Index assigns a score between 1 and 5 after performing textual forensic analysis of annual reports. Table 2 provides details on how the score is calculated.

Table 2: The 5-Point AI Maturity (AIMI)

Score	Level	Operational Definition	Verbal Statements / Pointers in the reports
1.0	Nominal	Superficial mentions of technology without strategic investments.	AI is the future, Exploring digital, Vision for technology.
2.0	Aspirational	Formulation of digital roadmaps or technology committees.	Digital roadmap, Evaluating vendors, IT Strategy Committee.
3.0	Functional	Execution of specific pilot projects or strong applications.	Pilot project for process improvement, Agentic AI creation, Chatbot creation.
4.0	Integrated	Scaling of AI across core business units and operations.	Predictive maintenance, vision-based security system, robot processes, optimized supply chain.
5.0	Frontier	R&D led AI, proprietary models, and Center of Excellence (CoE) for AI adoption.	Indigenous RTOS, GenAI for design, AI Patents.

Source: Authors' development based on Vial (2019), Mikalef & Gupta (2021), Cao et al. (2023), and the proposed AI maturity framework.

Textual Data

We collected 140 Annual Reports of 14 Maharatnas for the period 2016–2025 and 70 investor presentations for the period 2021–2025. To process this corpus of approximately 50,000 pages, we developed a unique textual forensic robot researcher pipeline using a Local LLM - Meta Llama 3.2. To validate the results, additionally we use another Local LLM deepseek-r1:8b. Our choice of a Local LLM over cloud-based APIs is driven by two factors: (i) Data Privacy, and (ii) Reproducibility.

The Extraction Protocol

We implemented a two pass Retrieval Augmented Generation (RAG) logic to ensure scoring accuracy:

- Pass 1 - Keyword Filtering: A Python-based pre-processor scanned each report for high signal clusters (e.g., AI, ML, Neural, Intangible Assets, R&D Annexure).
- Pass 2 -Contextual Reasoning: The LLM was prompted to perform Chain-of-Thought (CoT) reasoning. It was required to explain why it assigned a specific maturity score based on the extracted text before outputting the final JSON.

To ensure inter-rater reliability, we manually audited a random 10% sample (14 annual reports and seven investor presentations). The Local LLM assigned scores (Llama 3.2 & Deepseek-r1:8b) showed a 92% alignment with our ratings, confirming the robustness of the instrument.

Dependent Variable and Econometric Specification

The final dataset is a balanced panel (N = 14, t = 10, n = 140). We utilize a Panel Fixed-Effects (FE) regression model to evaluate the impact of AI maturity on financial resilience, market valuation, human capital productivity, and operational efficiency. The FE model is superior for this study as it controls for time-invariant unobserved heterogeneity across the Maharatnas. We consider four distinct dependent variables:

- Financial Resilience Z-Score: Measured using the Altman Z-Score (1968) formula.
- Market Value (Tobin's Q): This measures the digital premium awarded by investors.
- Human Capital Productivity (HC_Prod): This measures the augmentation effect of AI on employee efficiency.
- Operational Efficiency (OER): This measures the operational efficiency attained due to AI adoption.

Econometric Models

- Model 1 (Financial Resilience):

$$Z_{Score_{i,t}} = \alpha + \beta_1\left(AIMI_{i,t-1}\right) + \beta_2\left(Controls_{i,t}\right) + \gamma\left(Post_{2020}\right) + \delta_i + \epsilon_{i,t} \qquad \text{eq. (1)}$$

- Model 2 (Market Valuation):

$$Tobin_{Q_{i,t}} = \alpha + \beta_1\left(AIMI_{i,t-1}\right) + \beta_2\left(ROA_{i,t}\right) + \beta_3\left(Size_{i,t}\right) + \delta_i + \epsilon_{i,t} \qquad \text{eq. (2)}$$

- Model 3 (Human Capital):

$$HC\_Prod_{i,t} = \alpha + \beta_1(AIMI_{i,t-1}) + \beta_2(Size_{i,t}) + \gamma(Post\_2020) + \delta_i + \epsilon_{i,t} \qquad \text{eq. (3)}$$

- Model 4 (Operational Efficiency):

$$OER_{i,t} = \alpha + \beta_1(AIMI_{i,t-1}) + \beta_2(Asset\_Turnover_{i,t}) + \delta_i + \epsilon_{i,t} \qquad \text{eq. (4)}$$

where: $\mathrm{AIMI}_{i,t-1}$: The 1-year lagged AI Maturity Index (capturing the gestation period of technology); $\mathrm{Z\_Score}_{i,t}$: Financial Resilience (Altman Z-Score); $\mathrm{Tobin\_Q}_{i,t}$: Market Valuation (Tobin's Q); $\mathrm{HC}_{\mathrm{Prod}_{i,t}}$: Human Capital Productivity; $\mathrm{OER}_{i,t}$: Operational Efficiency; δ_i: Entity-specific fixed effects; $\mathrm{Controls}$: Includes Firm Size ($\ln\mathrm{Assets}$) and Leverage ($\mathrm{Debt/Equity}$).

Altman Z-Score = 1.2(X_1) + 1.4(X_2) + 3.3(X_3) + 0.6(X_4) + 0.999(X_5)

X_1 (Liquidity): $\frac{\text{Net Working Capital}}{\text{Total Assets}}$; X_2 (Cumulative Profitability): $\frac{\text{Retained Earnings}}{\text{Total Assets}}$; X_3 (Operating Efficiency): $\frac{\text{PBDITA}}{\text{Total Assets}}$; X_4 (Solvency): $\frac{\text{Market Capitalization}}{\text{Total Liabilities}}$; X_5 (Asset Productivity): $\frac{\text{Total Sales}}{\text{Total Assets}}$

Tobin's Q = Total Assets / (Market Capitalization + Total Debt);

Human Capital Productivity = Employee Cost / Total Income;

Operating Expense Ratio (OER) = Operating Expenses/ Total Income.

We source financial data of 14 Maharatnas from CMIE ProwessIQ. These data include, total sales, total assets, total liabilities, net worth, and few more that help us to calculate metrics of dependent variables. This secondary financial data allows us to perfectly matched panel between our AI Maturity Index Scores and the audited financial results.

We apply a forensic cleaning protocol to our final dataset to ensure econometric validity. We utilize a numeric coercion protocol via Python to handle the blank space. Missing values were treated using listwise deletion, ensuring that each regression model is based on a clean, complete case analysis. To control for the gestation period of technology investment, the independent variable (AI Maturity Index) was lagged by one year (*t-1*) in all econometric specifications.

3. Empirical Results

3.1 Descriptive Statistics

In Table 3 we present sector wise total income, total assets, and market capitalization of Maharatnas. It provides clear evidence of immense economic contribution of Maharatnas to the Nation. Oil-Gas sector followed by Mines-Minerals emerge as the primary engine of the economy both in terms of total income and market capitalization with ₹96.85 lakh crores and ₹12.08 lakh crores, and ₹32.76 lakh crores and ₹21.24 lakh crores respectively during the cognitive period (2021-25). We notice a significant jump in the market capitalization of defence sector; while its total income and total assets remain stable between the two periods, its market capitalization nearly tripled from ₹2.51 lakh crores to ₹8.95 lakh crores, majorly due to phenomenal surge in HAL market capitalization. This provides evidence of how capital markets react to the CPSEs technological innovations. Our textual forensic audited performed using RAG model reveal that during cognitive period HAL aggressively implemented AI in their product development and shown notable development in indigenous technology and autonomous systems.

Table 3: Descriptive Statistics

Amount. Rs. Crores				
Total Income				
Year	Defence	Mines and Minerals	Oil and Gas	Service
2016 - 2020	234,815	726,374	5,612,128	212,951
2016	44,619	129,127	958,602	33,631
2017	47,201	140,519	1,049,126	37,786
2018	47,355	130,264	1,049,126	37,866
2019	50,775	150,164	1,177,873	48,198
2020	44,864	176,301	1,377,401	55,470
2020 - 2025	233,980	1,208,772	9,685,292	311,572
2021	39,262	172,029	1,231,305	57,356
2022	45,063	227,265	1,766,345	58,488
2023	49,011	264,336	2,265,781	62,238
2024	49,011	270,183	2,279,445	65,537
2025	51,633	274,959	2,142,416	67,952
Total Assets				
Year	Defence	Mines and Minerals	Oil and Gas	Service
2016 - 2020	653,037	2,058,994	4,198,477	3,807,295
2016	130,454	359,894	733,049	647,832
2017	130,064	383,325	793,387	683,561
2018	127,959	383,325	793,387	683,561
2019	130,141	420,277	882,578	782,493
2020	134,419	512,172	996,076	1,009,848
2020 - 2025	729,315	2,811,053	6,226,895	5,982,270
2021	129,846	514,143	1,075,261	1,099,498
2022	137,122	544,348	1,180,841	1,110,692
2023	149,622	577,407	1,288,724	1,210,869
2024	149,622	577,407	1,277,526	1,210,869
2025	163,102	597,747	1,404,544	1,350,342
Market Capitalisation (Mcap)				
Year	Defence	Mines and Minerals	Oil and Gas	Service
2016 - 2020	251,820	1,478,316	2,626,471	729,404
2016	47,666	308,401	435,096	111,858
2017	61,659	343,865	662,913	177,422
2018	67,616	344,902	643,206	148,789
2019	49,815	302,037	581,483	166,297
2020	25,064	179,111	303,773	125,038
2020 - 2025	895,973	2,124,642	3,276,320	1,626,965
2021	50,242	216,152	415,310	168,745

Market Capitalisation (Mcap)				
Year	Defence	Mines and Minerals	Oil and Gas	Service
2022	66,911	284,341	529,273	205,242
2023	115,716	335,876	555,697	227,900
2024	308,595	648,479	906,273	505,149
2025	354,510	639,794	869,768	519,930

Note: Amounts are reported in Indian Rupees (₹ crore) and aggregated by sector for the foundational (2016–2020) and cognitive (2021–2025) periods.
Source: Authors' calculations based on CMIE ProwessIQ financial data.

Furthermore, we notice a significant increase in total assets of Service/Finance and Oil-Gas sectors between foundational period and cognitive period. The asset bases of Service/Finance grown to ₹59.82 lakh crores and Oil-Gas sector to ₹62.26 lakh crores. During the covid shock all the sectors witness drop in total income, total assets, and market capitalization. However, with in a short period all the sectors recovered. Role of technological investments and AI adoption helped this recovery and growth. During the cognitive period companies in mines-mineral and oil-gas implemented AI technologies like digital twins, smart grids etc.

In Table 4 we present the average scores of AI Maturity Index, Z-Score, Tobin's Q, Human Capital and Operational efficiency for the foundational period and cognitive period. As hypothesized, we notice a significant improvement in AI Maturity Index from 3.31 (2016-2020) to 4.20 (2021-2025). This 27 percent increase in AI Maturity Index indicates that Maharatnas have transitioned from simple digitization to intelligence. We also observe significant surge in human capital, indicating that Maharatnas we able to leverage high on their human resources.

Table 4: AI Maturity and Performance Indicators by Period

Period	Maturity_Score	Z_Score	Tobin_Q	Human_Capital	Opr_Exp_Ratio
2016-2020	3.31	3.49	1.29	31.47	0.62
2016	3.21	3.76	1.31	35.98	0.62
2017	3.46	3.94	1.51	29.29	0.62
2018	3.46	3.91	1.49	27.80	0.64
2019	3.07	3.30	1.30	30.04	0.60
2020	3.36	2.51	0.83	34.24	0.61
2020-2025	4.20	3.45	1.36	44.55	0.62
2021	4.07	2.47	0.89	29.17	0.62
2022	4.29	3.05	1.02	39.71	0.60
2023	4.14	3.15	1.13	51.31	0.64
2024	4.14	4.32	1.92	55.00	0.63
2025	4.36	4.25	1.82	47.55	0.62

Note: Reported values represent period averages for the AI Maturity Index, Altman's Z-Score, Tobin's Q, Human Capital Productivity, and Operating Expense Ratio.
Source: Authors' calculations based on AI Maturity scores and CMIE ProwessIQ financial data.

These results also indicate a strong relationship between AI Maturity, financial resilience, and market valuation of Maharatnas. Akin to increase in AI maturity index these scores also increased. The Altman Z Score witness a trough (2.51) during pandemic period; however, it recovered sharply during cognitive period and reach to 4.32 by 2024, this is in line with the peak AI maturity index. Correspondingly, Tobin's Q rise from 1.29 to 1.36, peaking at 1.92 in 2024. These results indicate that while the market is initially sceptical about CPSEs investments and adoption of AI, slowly they realised the potential benefits of digital intelligence. Interestingly, the operating expense ratio remains stagnant at 0.62 during the foundational and cognitive periods, supporting our gestation period paradox hypothesis, where AI maturity stabilizes the company's health and improves human capital before it substantively reduces the cost to income ratio.

3.2 Longitudinal Analysis of AI Maturity

Results present in Table 5 show that there is significant increase in AI Maturity Index and Human Capital between foundational period and cognitive period. The t-Stat for these two variables is significant at one percent level. Moreover, there is an increase in average score of Altman's Z score and Tobin's Q but not statistically significant. These preliminary results support our premise of transition from digitization initiatives like computerization, ERP implementations to integrated machine learning and autonomous systems.

A paired-sample t-test results of AI Maturity Index (t = 6.14, p < 0.00) confirm a statistically significant change in the AI Maturity post 2020. This result supports our Hypothesis 1, indicating that the external shocks of the early 2020 functioned as a stimulus for a cognitive turn within the Maharatnas.

In Post Covid period we see a significant economic shift in AI adoption among Maharatnas. There is significant jump in AI adoption scores from 2.45 to 4 and 87% of the enterprises are actively using AI for process improvements and cost cutting. For example, ONGC adopted AI-led deep-water drilling and seismic data interpretation and invested about ₹125 crores for IT modernization. Similarly, Oil India adopted AI driven applications in reservoir monitoring and production enhancement. NTPC adopted AI driven employee engagement bot. HAL developed drones and automated aircraft defect detection technologies using AI.

Table 5: t Test Results

Variable	Average Score				
	Cognitive Period	Foundational Period	t Stat	p Value	df
AI Maturity Index	4.20	3.31	6.14	0.00	69
Altman Z Score	3.45	3.49	0.10	0.46	69
Tobin's Q	1.36	1.29	0.41	0.34	69
Human Capital	44.55	31.47	3.84	0.00	69
Operational Efficiency	0.62	0.62	0.22	0.41	69

Note: Independent-sample t-tests compare the average values observed during the foundational (2016–2020) and cognitive (2021–2025) periods.

Source: Authors' calculations.

3.3 Multivariate Panel Regression Results

To examine the causal relationship between AI maturity and firm outcomes, we utilised a Panel Fixed-Effects (FE) model to control for unobserved entity-specific heterogeneity. The primary results are presented in Table 6.

Table 6: Panel Fixed-Effects Regression Coefficients

Dependent Variable: Altman's Z-Score						
	Parameter	Std. Err.	T-stat	P-value	LCI	UCI
const	4.28	13.79	0.31	0.76	-23.04	31.61
Lagged_Maturity	0.36	0.18	2.02	0.04	0.01	0.72
Firm_Size	-0.13	1.19	-0.11	0.92	-2.48	2.23
DE	-0.39	0.52	-0.74	0.46	-1.43	0.65
Post_2020	-0.22	0.49	-0.45	0.65	-1.20	0.76
Observations: 125 | Within R-Squared: 0.04						
Dependent Variable: Tobin's Q						
	Parameter	Std. Err.	T-stat	P-value	Lower CI	Upper CI
const	-4.00	5.96	-0.67	0.50	-15.81	7.82
Lagged_Maturity	0.13	0.08	1.62	0.10	-0.03	0.28
ROA	0.09	0.02	6.11	0.00	0.06	0.12
Firm_Size	0.35	0.51	0.70	0.49	-0.65	1.36
Post_2020	-0.23	0.21	-1.09	0.28	-0.65	0.19
Observations: 124 | Within R-Squared: 0.29						
Dependent Variable: Human Capital Productivity						
	Parameter	Std. Err.	T-stat	P-value	Lower CI	Upper CI
const	-655.14	130.44	-5.02	0.00	-913.69	-396.58
Lagged_Maturity	-2.44	1.69	-1.44	0.15	-5.79	0.92
Firm_Size	59.38	11.17	5.31	0.00	37.23	81.53
Post_2020	-2.32	4.61	-0.50	0.62	-11.46	6.81
Observations: 125 | Within R-Squared: 0.33						
Dependent Variable: Expense Ratio						
	Parameter	Std. Err.	T-stat	P-value	Lower CI	Upper CI
const	1.08	0.47	2.28	0.02	0.14	2.01
Lagged_Maturity	0.01	0.01	0.98	0.33	-0.01	0.02
TATR	0.02	0.03	0.61	0.55	-0.05	0.09
Firm_Size	-0.04	0.04	-1.04	0.30	-0.12	0.04
Post_2020	0.01	0.02	0.54	0.59	-0.02	0.04
Observations: 125 | Within R-Squared: 0.02						
Summary						
Model	Model (DV)	AI Coeff	P Value	R_Sqr_With	Obs	Sig.
1	Z_Score	0.36	0.04	0.05	125	**
2	Tobin_Q	0.13	0.10	0.30	124	*
3	Human_Capital	-2.44	0.15	0.33	125	ns
4	Opr_Exp_Ratio	0.01	0.33	0.02	125	ns

Note: Fixed-effects panel regressions estimate the impact of the one-year lagged AI Maturity Index on financial resilience, market value, human capital productivity, and operational efficiency while controlling for firm-specific characteristics. Robust standard errors are reported. Statistical significance: * $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$.

Source: Authors' calculations based on AI Maturity scores and CMIE ProwessIQ financial data.

The estimation for Model 1 provides empirical evidence that Lagged AI Maturity has a statistically significant positive impact on Financial Resiliency ($\beta = 0.36$, $p < 0.05$). For each incremental unit of AI Maturity achieved, the Altman Z-score improves by approximately 0.36 points in the following fiscal year. Model 2, examining Market Valuation, yields a coefficient of 0.12, which is statistically significant at the 10% level, indicating a directional but emerging relationship between AI maturity and market valuation.

To confirm these results, we verified Maharatnas investments in IT enabled services, Software Applications, and R&D expenses over the study period. We notice a noteworthy increase in the R&D expenses in cognitive period compared to foundational period. In case of Coal India, R&D expenses surged phenomenally (700%), in case of NTPC it is 360% increase. Defence sector company HAL has 129% surge in R&D expenses. The R&D expenses ranged between ₹100 crore to ₹2,500 crores. As much of these investments are incurred post covid on a continuous basis, we see a gradual positive impact of these on bottom line and market value of the company. However, we opine that the full benefits of these investments will be astonishing in coming years to come. But we do not find any statistically significant impact in the fixed-effects specification of AI Maturity on human capital and operating expenses.

4. Discussion

Our analysis of Maharatnas during the period 2016-2025 provides a strong support of the cognitive pivot of AI Maturity in Indian context. The fiscal year 2019-2020 and few months in the fiscal year 2020-2021 served as a critical external stress test, where financial resilience and market valuation reached a decadal lower point (Z score 2.51 & Tobin's Q 0.83). However, the simultaneous and stable climb in the AI Maturity Index rising from 3.36 in 2020 to a peak of 4.36 by 2025 acted as the initial coordinative mechanism for a robust, V-shaped recovery. By 2024, the sharp rebound to a Z-score of 4.32 and a doubling of the market valuation (Tobin's Q 1.92) suggest that AI Maturity has effectively transformed the Maharatnas. This recovery is further validated by the 41% surge in human capital productivity (31.47 to 44.55), supporting our hypothesis that the AI intelligence dividend in the CPSEs is representing a profound growth of the existing workforce, allowing these CPSEs to extract significantly higher value from their massive human asset.

The significance of our study's Altman's Z-score model supports the theoretical propositions of Resource Orchestration Theory (Sirmon et al., 2011). The results suggest that AI maturity serves as a dynamic capability, allowing Maharatnas to reconfigure assets to mitigate financial distress risk. Triangulating these results with our RAG based qualitative forensics, we observe specific procedures at play. For instance, NTPC's implementation of AI driven predictive maintenance which reported annual savings of over ₹850 crores, provides a concrete example of how artificial intelligence maturity reduces operational costs and improves the profitability components of the Z-score. Similarly, BPCL's Project Anubhav demonstrates the use of AI to maintain retail margins, thereby defending the firm from commodity price volatility.

The marginal significance of the Tobin's Q model indicates a persistent valuation gap in the Indian equity market. Despite the documented improvements in structural resiliency, the market appears slow to incorporate the value of intangible intelligence into the pricing of Maharatnas. This aligns with Institutional Theory (DiMaggio & Powell, 1983), where digital adoption might be viewed by external stakeholders as coercive compliance with national policy rather than a substantive value driver. Our findings suggest that while the textural forensic analysis can identify deep technological commitments in R&D annexures, traditional market participants remain attached to cyclical commodity valuations.

The Maharatnas are investing in AI to transform various business processes, some of these investments are made directly by the companies and some of these are investments are through start-up funding of AI start-ups. For example, ONGC invested in six start-ups during various series. Similarly, BPCL also invested in start-up. Many of these investments range between ₹10 crore and ₹1,000 crore and gestation periods range between one year to five years. The impact of these results on financial resilience will also take few years. However, the market may react to these instantly, either positively or negatively depending on the trends in AI technological developments. So, akin to digitization, artificial intelligence investments will transform the businesses, enhance revenues, minimizes costs and will have positive impact on financial resilience in future.

The non-significant and occasionally negative coefficients observed in the Human Capital and Operational Efficiency models deserve a more nuanced theoretical interpretation. The negative coefficient in the Service sector ($\beta = -4.61$, $p = 0.05$ in sub-group analysis) is consistent with the Modern Productivity Paradox (Solow, 1987) and recent observations by Brynjolfsson et al. (2024) regarding the AI J-Curve.

This divergence suggests that Maharatnas, particularly in the Service and Finance sectors are currently in a gestation phase. The high initial adjustment costs, including the acquisition of specialized human capital and the restructuring of legacy data systems, appear to suppress immediate productivity ratios. The realization of efficiency gains from AI in Maharatnas often lags implementation by several years, as the organization requires time to develop complementary assets.

From a methodological perspective, this paper validates the use of Local Large Language Models (LLMs) for forensic textual analysis in accounting research. The inter-rater reliability between the Llama 3.2 model and the authors demonstrates that automated maturity scoring can effectively mitigate the AI Washing noise identified by Cao et al., (2023). This approach provides a scalable and longitudinal alternative to bag of words analysis, enabling researchers to quantify intangible firm characteristics that are often excluded from traditional financial datasets.

Based on the results of our study, the following recommendations are made. Regulators should insist the disclosure of AI related capital investment and projected impact on financial health by companies in their annual reports. The Government, being the major stakeholder of the CPSEs should come up with sector specific policies and guidelines that will help CPSEs to actively use AI for process improvements, safety and security and robotic applications. These guidelines should be targeted improving the financial resilience. Furthermore, Maharatna boards should initiate high resilience experiments in predictive maintenance, cognitive inventory optimization, and automated forensic auditing to derive evidence-based improvements in operational efficiency and retained earnings.

Finally, Maharatnas leadership must proactively quantify and communicate AI investments, benefits, process improvements, cost savings in earnings calls to help investors to price these. CPSEs must pair AI investment with intensive human capital upskilling, treating workforce literacy as the critical bridge required to cross the J-Curve implementation dip and unlock the long-term intelligence dividend.

Conclusion

This paper provides a comprehensive longitudinal analysis of cognitive AI transformation in Indian Maharatnas. By fusing textual forensic analysis with financial econometrics, the study proves that there is a transition from simple digitization to AI intelligence in Maharatnas which accelerated post covid period. Using a local LLM a multidimensional AI Maturity Index is built and considered as an explanatory variable. The significant positive relationship between lagged AI Maturity Index and Altman's Z-score confirms that artificial intelligence adoption in Maharatnas is not merely a symbolic response to institutional pressures, but a robust mechanism for mitigating financial distress and optimizing asset health.

On the other side, this paper brings out two important issues. First, Maharatnas are currently navigating the J Curve transformation. The high initial costs of AI investments, training human capital, experimenting with different process improvements currently outweigh immediate efficiency returns. Second, the valuation gap reveals an information asymmetry in the Indian capital markets. While the textual forensic analysis of annual reports and investor presentations identifies deep technological integration at the operational level, the market fails to fully price the artificial intelligence premium of these Maharatnas. HAL is an exception to this.

Theoretically, this paper extends the knowledge of Resource Orchestration Theory by demonstrating how CPSEs can leverage cognitive resources to sustain macroeconomic volatility. Methodologically, this paper pioneered the use of Local LLM based textual forensics as a scalable, private, and objective instrument for longitudinal accounting research. This approach offers a new standard for quantifying intangible maturity in corporate disclosures, moving beyond simple keyword matching toward semantic reasoning. It is opined that the AI investments made during post covid period and early AI adoption years will yield substantial efficiency benefits in the coming years. By orchestrating AI as a core strategic capability rather than a peripheral IT project, the Indian public sector enterprises can redefine their role as a global leader in intelligence driven industrial resilience.

Credit Authorship Contribution Statement

Yelamanchili, R. K. conceived and designed the study; developed the research framework and the AI Maturity Index (AIMI); collected and curated the textual and financial datasets; designed and implemented the local large language model (LLM)-based forensic analysis pipeline; performed the econometric analysis; interpreted the results; drafted, reviewed, and revised the manuscript; and approved the final version for publication.

Acknowledgments/Funding

No Funding Received

Conflict of Interest Statement

The authors declare that they have no conflict of interest.

Data Availability Statement

The data supporting the findings of this study are derived from publicly available sources. Annual reports of the sampled Indian Maharatna enterprises are available through the respective corporate websites and the Bombay Stock Exchange (BSE). Financial statement data and financial ratios were obtained from the CMIE ProwessIQ database, which is available through institutional subscription. The AI Maturity Index (AIMI) scores were generated by the author through forensic textual analysis of these publicly available corporate disclosures. Processed data supporting the findings are available from the corresponding author upon reasonable request.

Ethical Approval Statement

This study is based exclusively on publicly available corporate disclosures and secondary financial data. It did not involve human participants, personal data, interviews, surveys, experiments, or animal subjects. Consequently, ethical approval and informed consent were not required under applicable institutional and international research ethics guidelines.

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