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An Empirical Investigation into the Nexus Between Industry 4.0 Adoption and Financial Performance: Evidence from Listed Indian Manufacturing Firms

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ABSTRACT
Industry 4.0 has emerged as a critical driver of technological modernisation in manufacturing, yet empirical evidence on its financial impact remains inconsistent, largely due to the dominant reliance on accounting-based indicators that fail to capture the long-term, intangible value created through digital transformation. Existing studies note this limitation but provide limited market-based evidence, especially in emerging economies. Addressing this gap, the present study examines how Industry 4.0 investments influence firm performance by employing Tobin's Q as a forward-looking indicator of market valuation. Using a longitudinal dataset of 58 NSE-listed Indian manufacturing firms (2011–2024), the study identifies digital adoption through text-mined disclosures and combines the resulting panel data with managerial survey insights to ensure triangulated interpretation. The findings align with resource-based and dynamic capability theories, demonstrating that Industry 4.0 investments enhance perceived future value. By integrating market-based financial analysis with qualitative managerial evidence, this study provides novel empirical clarity on how capital markets evaluate digital transformation within India's manufacturing sector..
Keywords: Industry 4.0, digital transformation, Tobin's Q, market-based performance, manufacturing firms, India, panel data analysis

1. INTRODUCTION:

The rapid diffusion of Industry 4.0 (I4.0) has transformed the global manufacturing ecosystem. It has done so by integrating cyber-physical systems, advanced robotics, big data analytics, cloud platforms, and artificial intelligence into contemporary production architectures (Guo et al., 2021a; Ilin et al., 2021). The literature describes this digital industrial paradigm as the convergence of the Internet of Things, cyber-physical systems, automation, 3D printing, augmented reality, blockchain, and artificial intelligence (Erol et al., 2016), (Calabrese et al., 2022). This convergence has redefined how manufacturing firms plan, operate, and scale their processes. The emergence of smart, autonomous, and interconnected factories illustrates this shift (Pagès et al., 2025). I4.0 is expected to enhance productivity, improve responsiveness, stimulate innovation, and strengthen firm-level performance. (Calış Duman & Akdemir, 2021; Li et al., 2020; Szász et al., 2020; Tortorella, Giglio, & van Dun D H, 2019)

Despite the claims of positive outcome, empirical research remains divided on whether digital transformation yields measurable financial benefits (Benedek et al., 2025). Consultancy reports and grey literature (Max Blanchet & Thomas Rinn, 2014) often forecast substantial gains in profitability and shareholder value; yet academic studies present conflicting results. Contemporary research increasingly interprets this inconsistency as evidence of a **digitalization paradox (Benedek et al., 2025)**, a concept that parallels the earlier **productivity paradox**, in which substantial technological expenditures failed to produce immediate increases in measured output (Brynjolfsson, 1993). Scholars argue that this paradox emerges from several underlying mechanisms. These include persistent challenges in capturing digital gains through conventional productivity metrics, delays between technology deployment and realized benefits, and the requirement for complementary organisational and strategic investments that enable digital tools to yield value (Dedrick et al., 2003; Frank et al., 2019a). A growing body of empirical work further indicates that the economic returns associated with Industry 4.0 are shaped by internal conditions such as a firm's dynamic capabilities, its ability to balance exploratory and exploitative innovation, the strategic clarity of its leadership, and the prevailing organisational culture (Munir et al., 2023; Orji & Liu, 2020). These insights underscore that these digital technologies, in isolation, are insufficient to ensure superior financial or operational outcomes without supportive managerial and organisational infrastructures.

These ambiguities are even more visible in emerging economies such as India (R. Kumar et al., 2020). The manufacturing sector has entered a period of accelerated modernization while simultaneously contending with uneven digital readiness, gaps in workforce skills, and the substantial capital required to establish advanced digital infrastructure (Hackel et al., 2023; L. Kumar & Sharma, 2025; Siriwardhana & Moehler, 2023; Sony & Mekoth, 2022). Although large companies listed on the National Stock Exchange (NSE) particularly in sectors such as automotive, pharmaceuticals, engineering goods, and other asset-intensive industries have begun to integrate I4.0 capabilities into their operations, adoption remains inconsistent across industries and firms (Digalwar et al., 2024). Policy initiatives such as *Make in India* have encouraged a shift toward digital manufacturing, yet empirical insights on financial consequences remain limited, especially the studies are grounded in cross-sectional analysis. (Ghobakhloo, 2018)

A further gap in existing research concerns the heavy reliance on traditional accounting-based indicators for evaluating digital transformation outcomes. These metrics capture operational results but do not fully represent how investors interpret intangible benefits, future innovation potential, or shifts in market expectations (Chauhan et al., 2021; Tortorella, Giglio, & van Dun, 2019) .Additionally, the literature emphasizes that many benefits from digital transformation materialize only after firms cultivate complementary capabilities such as cross-functional integration, digital leadership, innovation ambidexterity, and mature data-management practices. (Teece et al., 2016; Warner & Wäger, 2019)

In response to these gaps, the present study investigates how I4.0-related investments influence market-based financial performance among leading NSE-listed Indian manufacturing firms over the period 2011-2024. The study employs a text-mining approach to extract information on digital technology adoption from annual report disclosures and links these insights with large-sample panel data on financial outcomes. This blended methodology allows for a rigorous examination of how capital markets evaluate and price digital transformation efforts. The findings contribute to both the resource-based view and dynamic capabilities theories by conceptualizing I4.0 as a capability-enhancing strategic asset whose value emerges cumulatively and becomes evident only when firms develop appropriate complementary structures and practices. The contribution of this study is two-fold: first, methodologically, it introduces a market-based view of performance into I4.0 research for listed Indian manufacturing organizations; second, empirically, it examines whether I4.0 investments are value-creating from investors' perspective, beyond operational or accounting gains.

2. LITERATURE REVIEW

Industry 4.0 (I4.0) represents a significant technological transformation of manufacturing through the integration of cyber-physical systems, the Internet of Things, automation, advanced analytics, artificial intelligence, blockchain and augmented or virtual reality. These technologies create highly connected, data-driven and autonomous production systems expected to deliver substantial operational and financial gains(Arcidiacono & Schupp, 2024). Existing research consistently describes digitalization as enhancing controllability, predictability, and synchronization of production processes (Guo et al., 2021b; Olsen & Tomlin, 2020). Yet, the magnitude and reliability of resulting financial benefits remain contested, creating a persistent gap between operational improvements and measurable firm-level financial outcomes.

2.1 Theoretical Foundations: Resource-Based and Dynamic Capabilities Perspectives

Most empirical work on I4.0 performance is grounded in the resource-based view and dynamic capabilities. I4.0 technologies are conceptualized as strategic, capability-enabling resources that contribute to performance when integrated with organizational processes and competencies (Estensoro et al., 2022; Gupta et al., 2020). Empirical studies highlight innovation ambidexterity as a central mechanism through which I4.0 adoption translates into competitive advantage, showing that the interplay between digital technologies and innovation capabilities amplifies performance effects (Ballestar et al., 2021; Oduro & De Nisco, 2024). Consistent with dynamic capabilities theory, firms benefit from I4.0 when they can sense emerging technological opportunities, seize them effectively and reconfigure internal processes to support new digital capabilities. Research demonstrates that I4.0 adoption generates stronger outcomes when complemented by innovation ambidexterity, leadership strength, cross-functional coordination, and organizational alignment. (Antony et al., 2023; Črešnar et al., 2023; Gao et al., 2020; Yang et al., 2020)

2.2 Mixed Financial Evidence and the Digitalization Paradox

Despite strong theoretical expectations, empirical findings on the financial consequences of I4.0 remain inconsistent. Some studies report positive associations between digitalization and performance (Alkaraan et al., 2022; Prodi et al., 2022; Yang et al., 2020), while others observe weak, mixed or non-significant effects (Cheng et al., 2023; Lin et al., 2023; Szász et al., 2020; Zhao et al., 2024). A subset of research even identifies adverse outcomes, contributing to the “digitalization paradox,” wherein substantial digital investments fail to yield proportional financial returns (Kohtamäki et al., 2020; Yonghong et al., 2023). This paradox echoes earlier observations in IT productivity research, including the “Solow paradox,” which noted similar disconnects between technology spending and productivity gains (Triplett, 1999). Thus, while operational improvements are well documented, the financial implications of I4.0 remain an empirical puzzle.

2.3 Consistent Operational Gains but Weak Short-Term Financial Translation

The literature overwhelmingly reports positive operational outcomes from I4.0 adoption. Studies document improved cost performance, quality, delivery speed, flexibility, and real-time visibility (Olsen & Tomlin, 2020; Zonta et al., 2020). Advanced analytics, sensors and predictive maintenance are shown to substantially enhance overall equipment effectiveness by reducing downtime and forecasting equipment health (N. Kumar & Kumar, 2019; Mathur et al., 2011). However, these operational improvements do not consistently translate into stronger accounting-based financial outcomes. For example, smart manufacturing practices enhance quality and delivery but may not yield higher profit margins (Lee et al., 2023). Instead, clearer evidence emerges for non-financial gains such as innovation, supply chain visibility and information transparency (Ballestar et al., 2021). Studies using textual analysis demonstrate that stock markets respond positively to firms' digital transformation disclosures, even when accounting indicators remain unchanged, suggesting that investors recognize strategic transformation value before it appears in financial statements. (Qinqin et al., 2023)

2.4 Measurement Limitations: Accounting Indicators and the Case for Market-Based Metrics

Research on I4.0 performance predominantly uses accounting ratios such as return on assets (ROA), return on equity (ROE), operating profit margin, net profit margin and asset turnover. Although these measures are standardized and widely adopted, they possess well-known limitations in capturing digital transformation outcomes. Accounting ratios reflect historical performance and are slow to incorporate intangible or long-term benefits arising from digitalization. Moreover, DuPont decomposition shows that ROA combines profitability and asset efficiency, potentially masking efficiency-driven improvements that do not immediately affect margins (Dehning & Stratopoulos, 2002). Several empirical studies acknowledge these limitations, noting that firms often exhibit no significant improvements in accounting-based profitability while still experiencing positive market reactions to digitalization (Frank et al., 2019b; Jardak & Ben Hamad, 2022). These insights reinforce the need for forward-looking financial indicators capable of capturing intangible value creation.

2.5 Time-Lag and Complementarity Effects

A recurring theme in the literature is the presence of time-lag effects between I4.0 adoption and measurable financial gains. Digital transformation requires substantial capital investment, specialized skills, and extensive process integration, delaying the realization of financial benefits (Benassi et al., 2022; Chae, 2015). Several studies show that I4.0 influences measures such as ROE only after a multi-year delay, while operational efficiencies precede financial performance improvements. Complementarity effects further explain inconsistent findings: I4.0 produces stronger performance outcomes when paired with supportive organizational capabilities, including innovation ambidexterity, leadership capability, cross-unit coordination, green culture, and open innovation practices. (Chavez et al., 2017; Dubey et al., 2015; Fujimoto et al., 2022; Sahoo et al., 2025)

2.6 Contextual Variation and Limited Evidence from India

The impact of I4.0 varies across firm types, competitive environments, and national contexts. Large firms tend to invest more aggressively in digital technologies, while SMEs adopt more gradually (Ganzarain & Errasti, 2016; M. Kumar et al., 2006). In emerging economies, private and large Chinese firms lead I4.0 adoption, with firms in less competitive Southeast Asian markets also exhibiting higher investment levels compared with advanced economies. These contextual variations indicate that results from developed countries cannot be automatically generalized to emerging economies such as India.

Despite India's strong policy focus on digital manufacturing, empirical studies on the financial consequences of I4.0 for Indian listed firms remain scarce. Existing research primarily examines MSMEs, supply chain digitalization and readiness frameworks rather than firm-level financial outcomes. Available empirical work highlights positive effects on operational performance such as quality improvements, asset utilization and reduced cycle times, particularly when digital tools are integrated with lean and process improvement practices (Hofer et al., 2012; Mittal et al., 2017; N.A.Q.M. et al., 2025). However, there is limited evidence on how I4.0 investments influence the **market value** of Indian manufacturing firms.

3. RESEARCH METHOD

This study employs a mixed-method empirical strategy to quantify the causal relationship between Industry 4.0 (I4.0) investments and firm-level financial performance within India's manufacturing sector. The approach integrates secondary panel data analysis with primary survey-based triangulation to strengthen construct validity and interpretive depth. Firm performance is operationalised through Tobin's Q, a market-based indicator that reflects forward-looking valuation of both tangible and intangible assets. This measure is well suited to I4.0 investments because advanced technologies such as AI, robotics, IoT, cloud systems, and cybersecurity typically generate long-horizon innovation and efficiency gains that are imperfectly captured by short-term accounting profits. Consequently, Tobin's Q provides a comprehensive proxy for market perceptions of digital transformation benefits and investor expectations about future cash flows.

Industry 4.0 investment is quantified using text mining of annual reports, focusing on explicit mentions of technological adoption across management commentary, directors' reports, and explanatory notes. These disclosures are converted into a binary independent variable, coded as 1 when I4.0-related terms appear and 0 otherwise. Control variables include leverage, liquidity, and firm size (proxied by logarithms of assets and employees), ensuring robust model specification and minimising omitted variable bias. To complement the secondary data, a Likert-scale questionnaire was administered to senior executives overseeing digital transformation, capturing managerial assessments of operational and strategic outcomes associated with I4.0 adoption. This triangulated design combines objective financial indicators with contextual managerial insights to deepen the explanatory power of the results.

3.1 Research Design

The research adopts a longitudinal panel design to leverage both cross-sectional and time-series variation among listed Indian manufacturing firms. The sampling frame began with the top 200 National Stock Exchange (NSE) listed companies by market capitalisation in manufacturing sector. Using industry classification and corporate disclosures, 58 manufacturing firms were isolated across a diverse set of sub-sectors, including electronics, metals and mining, automobiles, pharmaceuticals, defence manufacturing, construction materials, consumer goods, and oil and gas. This range captures both capital-intensive and technology-intensive segments of India's manufacturing ecosystem, thereby enhancing external validity.

I4.0 investment data were extracted through text mining algorithms that scanned for keywords related to smart manufacturing, robotics, digitalisation, artificial intelligence, cloud computing, cybersecurity, and digital transformation. The binary nature of the variable reflects disclosure incidence rather than intensity, consistent with prior research leveraging narrative reporting for proxy construction. The primary independent variable I4.0 Investments was identified through text mining of annual reports, specifically scanning management discussion & analysis (MD&A), directors' reports, and notes to accounts for disclosures related to keywords like 'robotics', 'Smart Manufacturing', 'artificial intelligence', 'cybersecurity', 'cloud computing', 'digitalization', 'digital-transformation' etc. The independent variable was taken in binary form, 1 if there is a mention and 0 if not.

Data Selection and Sampling Framework

To empirically examine the relationship between Industry 4.0 (I4.0) investments and firm-level financial performance, we began by identifying the top 200 companies listed on the National Stock Exchange (NSE), ranked by market capitalization. From this initial set, we filtered for manufacturing sector firms using industry classification codes and company disclosures. The resulting final sample comprised 58 manufacturing companies, covering diverse sub-sectors including: Electrical Equipment Manufacturing, Construction Materials, Consumer Goods and FMCG, Oil & Natural Gas, Pharmaceuticals, Automobiles and Auto Components, Defence Equipment Manufacturing, Metals & Mining, Electronics, and Non-Ferrous Metals.

3.3 Data Sources

Firm-level financial data was collected from CMIE ProwessIQ and CMIE ProwessDX databases, which provide standardised, audited, and reliable time-series corporate financial statements. For each firm-year observation (2011–2024), we extracted:

Market Capitalization (share price x total outstanding shares)

Total Assets

Total Debt (sum of current liabilities and non-current liabilities)

Tobin's Q was employed as the proxy for firm financial performance, calculated as:

Tobin's Q= (Market Value of Firm + Book Value of Debt)/Total Assets

The market value of the firm was computed as market capitalization, while the book value of debt was obtained by summing current and non-current liabilities.

Control Variables and Justification

Table 1: Control Variables to ensure model robustness and avoid omitted variable bias.

Variable	Justification
Leverage (Debt/Assets)	Controls for the effect of financial structure on performance; highly leveraged firms may have constrained investment flexibility.
Liquidity (Current Assets / Current Liabilities)	Measures short-term financial health, which can affect the firm's ability to implement I4.0 projects.
Firm Size – proxied by log of total assets and employees	Larger firms typically have greater resources for digital adoption; log transformation controls for scale effects and reduces skewness.

Regression Model Specification

The panel data regression model was specified as:

$$
\begin{aligned}
ln(Tobin's)Q_{it} = \beta_0 + \beta_1\,(I4.0\ Investments)_{it} \\
+ \beta_2\,(Leverage)_{it} \\
+ \beta_3\,(Liquidity)_{it} + \beta_4 \ln(Assets)_{it} \\
+ \beta_5 \ln(Employees)_{it} + \alpha_i + \lambda_t \\
+ \epsilon_{it}
\end{aligned}
$$

Where:

α_i = firm-specific fixed effects (controls for time-invariant characteristics such as management style, location, culture)

λ_t = time fixed effects (controls for macroeconomic shocks, policy changes, business cycles)

ϵ_{it} = idiosyncratic error term

Table 2: Panel Regression Model Comparison

	Fixed Effects	Random Effects	Pooled OLS
Dep. Variable	Tobin's Q	Tobin's Q	Tobin's Q
Estimator	Panel OLS	Random Effects	Pooled OLS
No. Observations	740	740	740
Cov. Est.	Clustered	Unadjusted	Unadjusted
R-squared	0.9857	0.9866	0.9866
R-Squared (Within)	0.9862	0.9866	0.9862
R-Squared (Between)	0.9778	0.9861	0.9874
R-Squared (Overall)	0.9824	0.9862	0.9866

F-statistic	9178.3	1.08e+04	1.081e+04
P-value (F-stat)	0.0000	0.0000	0.0000
	===========	===============	============
Const.	0.1906 (6.0031)	0.1440 (16.733)	0.1345 (27.136)
I4.0it	0.1112 (39.579)	0.1121 (111.52)	0.1124 (98.126)
ln $(Assets)_{it}$	-0.0038 (-1.3119)	0.0008 (0.9876)	0.0021 (4.6548)
$(Leverage)_{it}$	0.0008 (0.0653)	0.0001 (0.0328)	-0.0022 (-0.7280)
$(Liquidity)_{it}$	0.1115 (52.071)	0.1110 (184.65)	0.1092 (186.36)
ln $(Employees)_{it}$	-0.0157 (-5.9476)	-0.0168 (-23.965)	-0.0174 (-37.783)

Table 3: Original Model (Tobin's Q) with Robust SE: OLS Regression Results

Dep. Variable	Tobin's Q	R-Squared	0.986
Model:	OLS	Adj. R-Squared	0.986
Method:	Least Square	F-Statistics	2147.
No. Observations	682	Prob (F-statistic):	0.00
Df Residuals:	676	Log-Likelihood:	1996.5
Df Model:	5	AIC:	-3981.
Covariance Type:	HC1	BIC:	-3954.

Table 4: OLS Regression Results

Variable	**Coefficient**	**Std. Error**	**t-stat**	**p-value**	**Lower 95%**	**Upper 95%**
Const.	0.1435	0.007	20.321	0	0.13	0.157
$I4.0_{it}$	0.1116	0.0014	80.171	0	0.109	0.114
ln $(Assets)_{it}$	0.0019	0.0006	3.401	0.001	0.001	0.003
$(Leverage)_{it}$	-0.0031	0.0036	-0.847	0.397	-0.01	0.004
$(Liquidity)_{it}$	0.1082	0.0025	43.416	0	0.103	0.113
ln $(Employees)_{it}$	-0.0179	0.0009	-19.079	0	-0.02	-0.016

Omnibus:	270.718	Durbin-Watson:	0.829
Prob (Omnibus):	0.000	Jarque-Bera (JB):	3725.080
Skew:	1.383	Prob (JB):	0.00
Kurtosis:	14.110	Cond. No.	165.

Table 5: Log-Transformed Model ln (Tobin's Q) with Robust SE: OLS Regression Results

Dep. Variable:	ln_TobinsQ	R-squared:	0.678
Model:	OLS	R-squared:	0.676
Method:	Least Squares	F-statistic:	130.1
No. Observations:	682	Prob (F-statistic):	1.91e-96
Df Residuals:	676	Log-Likelihood:	-559.51
Df Model:	5	BIC:	1158.
Covariance Type:	HC1		

OLS regression Results

Variable	**Coefficient**	**Std. Error**	**t-stat**	**p-value**	**Lower 95%**	**Upper 95%**
Const.	-2.5759	0.263	-9.786	0	-3.093	-2.059
I4.0it	1.6347	0.088	18.489	0	1.461	1.808

ln $(Assets)_{it}$	-0.0223	0.018	-1.23	0.219	-0.058	0.013
$(Leverage)_{it}$	-0.4817	0.125	-3.867	0	-0.726	-0.237
$(Liquidity)_{it}$	0.4192	0.07	5.971	0	0.281	0.557
ln $(Employees)_{it}$	-0.0693	0.017	-4.157	0	-0.102	-0.037

Omnibus:	522.817	Durbin-Watson:	1.012
Prob (Omnibus):	0.000	Jarque-Bera (JB):	11798.995
Skew:	-3.226	Prob (JB):	0.00
Kurtosis:	22.328	Cond. No.:	165

Logarithmic transformation was applied to continuous variables to:

Stabilise variance and address heteroskedasticity.

Normalise skewed financial variables.

Enable elasticity interpretation of coefficients.

Table 6: Variance Inflation Factor (VIF) for Multicollinearity Diagnostics

Feature	**VIF**
Const.	107.4455
I4.0it	1.069526
ln $(Assets)_{it}$	1.457346
$(Leverage)_{it}$	1.249861
$(Liquidity)_{it}$	1.212151
ln $(Employees)_{it}$	1.559462

We estimated Random Effects and two-way Fixed Effects panel regressions with two-way clustered standard errors to account for heteroskedasticity, serial correlation, and cross-sectional dependence. Results are highly consistent across specifications. Industry 4.0 investments show a strong positive effect on Tobin's Q ($\beta \approx 0.11$, $p < 0.001$), confirming the strategic role of digital transformation in enhancing firm value. Liquidity also has a robust positive impact ($\beta \approx 0.11$, $p < 0.001$). Firm size, measured by employees, exhibits a significant negative association with Tobin's Q, while leverage remains insignificant. The Hausman test ($\chi^2 = 6.02$, p = 0.42) supports the consistency of the RE estimator, but findings remain stable under FE. We therefore report both specifications, demonstrating robustness of the main results.

Results and Discussion

The panel regression results reveal a strong, statistically significant, and economically meaningful positive association between I4.0 investment and firm value. Across fixed-effects, random-effects, and pooled OLS estimations, the coefficient for I4.0 investment remains consistently positive at approximately 0.111, with extremely high statistical significance ($t \approx 39.6$, $p < 0.001$). This indicates that firms mentioning I4.0 technologies in their annual reports exhibit materially higher Tobin's Q ratios, suggesting that capital markets reward digital transformation with valuation premiums rooted in expectations of improved efficiency, reduced risk, and long-term growth prospects.

Liquidity also demonstrates a robust positive effect, reflecting that firms with stronger short-term financial positions are better positioned to implement or benefit from I4.0 projects. Firm size (measured through assets) shows inconsistent significance across specifications, while headcount exhibits a negative and significant association, potentially signalling coordination challenges or legacy system inertia in labour-intensive firms. Leverage remains broadly insignificant, indicating that capital structure does not materially distort the digital investment–valuation relationship.

Complementary OLS models using robust standard errors yield similar patterns, and logarithmic models *(R^2 = 0.678)* confirm the direction and significance of effects even under alternative functional forms. Absence of multicollinearity (VIF < 2) and model diagnostics confirm robustness.

Survey findings triangulate these quantitative outcomes. Managerial respondents consistently report substantial operational gains: efficiency (4.15 average), labour productivity (3.88), ROI (3.75), profit growth (3.65), and sales growth (3.58), with over two-thirds rating efficiency, productivity, and ROI improvements at or above 4 on a 5-point scale. Qualitative feedback further highlights real-time decision-making (75%), cost reduction (67.5%), customer satisfaction improvements (65%), and energy/material savings (62.5%) as key outcomes. Reported frictions including legacy integration challenges (55%), job displacement concerns (45%), and workforce resistance (40%) offer insight into variation in realised performance and inform the mechanisms through which digital investments translate into market value.

Taken together, the econometric estimates and managerial evidence collectively demonstrate that I4.0 initiatives are associated with enhanced firm value because they generate capability improvements that financial markets anticipate and price.

Theoretical & Practical implication

The findings of this study offer clear theoretical implications for understanding the strategic role of Industry 4.0 in firm performance. The consistent positive relationship between I4.0 disclosures and Tobin's Q provides empirical support for viewing digital transformation as a capability-enhancing strategic resource within the resource-based view, indicating that investors recognise and value these investments when they are communicated transparently. The results also reinforce dynamic capabilities perspectives, suggesting that markets reward firms not only for adopting advanced technologies but also for demonstrating the development of complementary organisational capabilities. The observed gap between immediate operational improvements and slower accounting-based financial responses further aligns with theoretical arguments that capability reconfiguration, absorptive capacity and complementary assets are essential for digital investments to translate into sustained financial value.

The practical implications of this study underscore the need for managers and policymakers to adopt a holistic approach to digital transformation. For firms, the evidence indicates that technology adoption alone is insufficient to generate sustained performance gains; instead, complementary capabilities such as leadership alignment, workforce upskilling, process redesign and cross-functional coordination are essential for realising the full value of Industry 4.0 investments. The strong positive effect of liquidity further highlights the importance of maintaining adequate financial buffers, as firms with stronger short-term financial positions are better equipped to undertake multi-year digital transformation programmes and absorb associated transition costs. The study also shows that disclosure practices play a strategic role: transparent and credible communication of digital initiatives can shape investor expectations and reduce information asymmetry, thereby enhancing market valuation. Managers should therefore articulate the strategic intent, expected benefits and governance structures of their I4.0 initiatives when reporting to stakeholders. For policymakers in emerging economies, the findings indicate that supporting complementary capability development through skills training, leadership programmes and organisational transformation support is crucial. Effective policy design should integrate incentives for technological investment with broader institutional support that facilitates organisational readiness and capability building.

4. CONCLUSION

The study provides robust empirical evidence that Industry 4.0 investments are positively associated with higher firm valuation in India's manufacturing sector. Using Tobin's Q as a market-based indicator and a fixed-effects panel design over 2011-2024, the findings consistently show that firms disclosing I4.0 adoption receive significant valuation premiums. These results remain stable across multiple estimators, diagnostic checks, and model specifications, underscoring the reliability of the conclusions. Survey-based triangulation further indicates that managers observe tangible improvements in operational efficiency, productivity, decision-making, and customer experience, precisely, the channels through which digital adoption enhances expected future cash flows.

Limitations: The binary disclosure-based measure captures firms' signalling of Industry 4.0 activity rather than the full depth of investment, yet it remains an appropriate and transparent proxy for understanding how markets respond to publicly communicated digital initiatives. Although the design is observational, the use of longitudinal panel data, firm fixed effects and extensive robustness checks strengthens the credibility of the findings, even if some residual endogeneity cannot be eliminated. The focus on 58 large, listed manufacturing firms ensures high-quality data, though it naturally limits generalisability to smaller firms with different digital maturity levels. The managerial survey enriches the analysis by providing contextual insights that financial data alone cannot capture, despite the possibility of perceptual bias. Finally, distributional characteristics of Tobin's Q required standard transformations, reflecting common challenges in market-based research, and addressed through appropriate statistical corrections.

Overall, the study confirms that capital markets recognise and reward digital transformation, validating I4.0 investments as strategic resources aligned with contemporary competitiveness imperatives. Although observational and reliant on disclosure proxies, the convergence of market-based evidence and managerial insights provides strong construct validity and a compelling rationale for sustained and well-governed I4.0 initiatives within the Indian manufacturing landscape.

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