International Journal of Computer Information Systems and Industrial Management Applications
ISSN 2150-7988 Volume 18(2) 2026 pp. 586-600
https://doi.org/10.70917/ijcisim-2026-2961
Article

IT Investment Intensity and Dynamic Profitability: Organisational and Operational Contingencies in Indian Manufacturing Firms

Mohit Saxena[1], Bikrant Kesari[2], Amit Banerji[3]
[1]Department of Management Studies, Maulana Azad National Institute of Technology, Bhopal, India
Email: saxenamohit.wtc@gmail.com
ORCID: https://orcid.org/0009-0003-9016-2299
Corresponding Author
[2]Department of Management Studies, Maulana Azad National Institute of Technology, Bhopal, India
ORCID: https://orcid.org/0000-0003-3363-3421
[3]Department of Management Studies, Maulana Azad National Institute of Technology, Bhopal, India
ORCID: https://orcid.org/0000-0002-2565-8736

Abstract: Digital-investment intensity has become a common line item in manufacturing accounts, yet its link to accounting profitability is rarely tested against the organisational and operating conditions under which spending actually occurs. This study asked whether, and under what conditions, digital-investment intensity was associated with the dynamic profitability of Indian manufacturing firms, examining financial slack, workforce intensity, energy-cost intensity, and asset turnover as candidate moderators. Annual firm-level data for 2014–2024 came from the CMIE Prowess database; the sample, 28,304 observations across 4,049 firms, was analysed with two-step difference GMM (Windmeijer-corrected robust standard errors, collapsed instruments, a lag window of two to three periods), benchmarked against dynamic pooled OLS, dynamic fixed effects, and fixed effects with Driscoll–Kraay standard errors. Profitability proved positively persistent, and in the base model digital-investment intensity carried no statistically significant independent association with return on assets. Financial slack helped profitability directly but left the digital-investment relationship unmoderated. Workforce intensity cut the other way at each level: a negative direct association coexisted with a positive, significant interaction that made the conditional digital-investment association less severe without ever turning it positive across the range examined. Asset turnover showed the reverse pattern — a positive direct effect alongside a negative conditioning relationship. Energy-cost intensity registered no significant role of either kind. Read together, the results point toward a selective, context-dependent account of digital-investment benefit realisation in emerging-economy manufacturing rather than an automatic profitability premium, and every claim above should be read as associational rather than causal.

Keywords: digital investment, firm profitability, organisational complementarity, manufacturing firms, dynamic panel data, difference GMM, India

1. Introduction

Software, information systems, and digital infrastructure now absorb a substantial share of manufacturing firms' capital budgets, but whether that spending shows up in accounting profitability is far from settled. Recent studies have reported positive, negative, delayed, and non-linear relationships between digitalisation and firm performance [1–5]. Part of the disagreement is definitional: a text-based digital-transformation index, a patent-based convergence measure, a survey score of digital maturity, and an accumulated stock of IT capability are four different things, none equivalent to the annual software and IT expenditure line firms actually disclose — so their profitability implications need not coincide.

There is also a productivity–profitability gap worth taking seriously. Despite the fact that none of this increase in output, processes, or organisational flexibility may be reflected in the return on assets in the company, a firm can still invest in IT to enhance these three areas without any of those increases being seen as a return [6, 7]. A model that looks only for a direct effect of digital spending on ROA can therefore miss the conditions that actually determine whether such an association appears at all.

Three gaps in the literature motivated this study. Disclosed software and IT expenditure relative to sales has drawn comparatively little attention next to broader digital-transformation indicators. Financial, organisational, and operating contingencies are rarely brought into the same model even though each plausibly matters: financial slack can supply flexibility, workforce expenditure may travel alongside the resources firms use to deploy new technology, energy costs can crowd out other spending, and asset turnover separates firms with different revenue-to-asset configurations — each capable of a direct profitability association quite different from its conditioning role for digital investment. Finally, profitability persists over time, and both lagged profitability and digital investment are plausibly endogenous, calling for a dynamic panel design that separates persistence from contemporaneous association while limiting bias from unobserved firm heterogeneity.

This left one central question: how is digital-investment intensity associated with the dynamic profitability of Indian manufacturing firms, and how is that association conditioned by financial slack, workforce intensity, energy-cost intensity, and asset turnover? The resource-based view supplies the underlying resource logic; organisational complementarity is the mechanism behind the interaction models; the IT benefit-realisation perspective explains why observable expenditure need not produce an immediate profitability premium; and the profit-persistence literature justifies the dynamic specification.

The empirical analysis was based on the data from the CMIE Prowess, which consists of 35,236 observations from 5,050 manufacturing firms between 2014 and 2024 in the dynamic sample and 28,304 observations from 4,049 manufacturing firms in the difference-GMM sample. The main estimator was two-step difference GMM with Windmeijer-corrected robust standard errors, instruments collapsed, and a lag window of two to three periods. Benchmark and robustness comparisons were made with dynamic pooled OLS and dynamic firm fixed effects (firm-clustered standard errors) and fixed effects with Driscoll–Kraay standard errors.

No automatic profitability premium from digital-investment intensity emerged from these results. Profitability was positively persistent, and the direct digital-investment coefficient failed to reach significance in the base model. Financial slack helped profitability directly without altering the digital-investment relationship. Workforce intensity hurt profitability directly, yet positively moderated the digital-investment association — making the negative conditional link less pronounced, though never reversing it, across mean plus or minus one standard deviation. Asset turnover helped profitability directly but carried a negative interaction with digital investment. Energy-cost intensity mattered in neither respect.

Four contributions follow from this design: observable software and IT expenditure intensity in place of a broad digital-transformation proxy; evidence that organisational and operating variables can pull in different directions depending on their direct versus interactive role; a dynamic profitability framework built on restricted internal instruments; and evidence from Indian manufacturing, setting firm-level digital-investment research has left comparatively unexplored.

The remainder of the article proceeds as follows. Section 2 develops the theoretical arguments and hypotheses. Section 3 describes the data and methods. Section 4 reports the empirical results, and Section 5 discusses their implications. Sections 6 and 7 set out theoretical and managerial implications, Section 8 addresses limitations and directions for future research, and Section 9 concludes.

2. Literature Review, Theoretical Framework and Hypotheses

2.1 Digital investment, profitability, and benefit realisation

Firm-level studies have generally reported more favourable IT-performance relationships than aggregate-level studies, though results depend on how IT is measured and which outcome is examined. Brynjolfsson and Hitt [8] associated computer capital with output using firm-level panel data, while Brynjolfsson and Hitt [6] argued that productivity gains may emerge only after organisational adjustment and need not translate directly into accounting profit. Dedrick et al. [7] similarly concluded that the evidence for firm-level productivity is stronger than the evidence for accounting profitability, and more sensitive to complementary inputs and implementation lags.

Recent manufacturing evidence remains mixed. Guan and Wang [5] reported a negative association between firm-level IT investment and performance that varied with digital-transformation level and CEO characteristics, while

Gao et al. [4] identified a U-shaped relationship between a patent-based digital-technology-convergence measure and financial performance. Studies using text-based digital-transformation indices, by contrast, have generally reported positive associations with accounting outcomes through cost, innovation, or efficiency channels [1–3]. None of these maps cleanly onto annual expenditure intensity, but the pattern as a whole lean toward a positive expectation, tempered by a clear warning against treating digital investment as automatically productive.

H1: Digital-investment intensity is positively associated with firm profitability.

The benefit-realisation perspective offers the principal explanation for these mixed findings: annual expenditure may precede process redesign, learning, integration, and complementary investment. Stratopoulos and Dehning [9] distinguished successful IT capability from expenditure alone, and Chen and Zhang [3] found that digital-transformation associations become more apparent with a lag — not evidence that such delays occur here, but reason to think current expenditure's profitability association may depend on organisational and operating conditions.

2.2 Resource-based view and organisational complementarity

The resource-based view holds that advantage arises not from possessing resources but from combining and deploying them in ways that are valuable and hard to imitate [10]. Bharadwaj [11] and Santhanam and Hartono [12] linked IT capability to superior accounting performance, though their capability measures differ from an annual expenditure ratio; Melville et al. [13] and Wade and Hulland [14] likewise positioned IT resources within broader systems of organisational capability.

Complementarity theory predicts something more specific: the marginal value of one input can rise or fall with the level of another [15]. Bresnahan et al. [16] found exactly this for IT investment and information-intensive workplace organisation, which moved together in their effect on output, and later work has pushed the same logic toward non-IT resources, higher-order capabilities, and organisational agility as additional conditions for digital value creation [17–20]. None of these studies treats the accounting moderators used here as capability measures in their own right, but collectively they give reason to test whether the DIT–profitability association shifts across firm contexts.

Expenditure and capability also part ways on timing. A firm books DIT the moment it commits resources, while the productive payoff depends on complementary routines that only accumulate over several periods — so a firm mid-installation can show a high DIT ratio well before operating benefits arrive, just as a firm with mature digital capability can keep performing well in a year when current spending is modest. That mismatch alone gives theoretical reason to expect a weak contemporaneous direct association, apart from any claim that digital systems are unimportant. Nor is it assured that complementarity works in both directions: a resource might have a positive direct coefficient without affecting the conditional DIT equation, and a resource might have a negative direct coefficient and yet weaken the conditional DIT equation. That asymmetry is why interaction estimates, not favourable main effects, carry the evidentiary weight here — a point underlying the financial-slack, workforce-intensity, and asset-turnover arguments below.

2.3 Financial slack

Slack has long been credited with two things: buffering firms against shocks and freeing up discretionary resources for investment [21] — though too much of it can dull managerial discipline, which is why the empirical record swings from straightforwardly positive to non-linear. Tan and Peng [22] and Lefebvre [23] both found inverted-U patterns; George [24] and Vanacker et al. [25] found that the relationship shifts with firm and institutional conditions; and Jin et al. [26] found slack cushioning firms through the COVID-19 shock, albeit with a slack measure not directly equivalent to the net-working-capital ratio used here.

A working-capital-based slack position may support profitability through liquidity and operational resilience, and may also facilitate complementary spending around digital projects; general financial flexibility, though, need not be deployed specifically for digital implementation.

H2: Financial slack is positively associated with firm profitability.

H3: Financial slack positively moderates the association between digital-investment intensity and firm profitability.

2.4 Workforce intensity

Workforce intensity — employee expenditure divided by sales — is an expenditure and cost-structure measure, not a direct measure of employee skill, training, human capital, or digital competence. Its direct profitability association is theoretically ambiguous: higher employee expenditure may compress margins, yet may also accompany revenue-generating activity.

Complementarity research suggests that organisational practices and workforce-related capabilities can condition IT returns [16, 17, 27] — indirect evidence, since these studies examine skills, practices, or capabilities rather than employee-expenditure intensity, but enough to support testing whether a labour-related expenditure context changes the DIT–profitability association.

H4: Workforce intensity is associated with firm profitability.

H5: Workforce intensity positively moderates the association between digital-investment intensity and firm profitability.

2.5 Energy-cost intensity and asset turnover

Energy-cost intensity, defined as energy expenditure divided by sales, differs from physical energy efficiency, carbon intensity, and environmental performance more broadly. Higher energy costs relative to sales would be expected to compress profitability, and Alavani et al. [28] reported a negative association between energy intensity and profitability among PAT-covered Indian manufacturing firms using a closely related cost measure. However, Jain and Kaur [29] showed evidence that is contrary to the above, for Indian metallic manufacturers, and Orțan [30] related overall utility costs to employment, exports and productivity, not directly to ROA.

H6: The profitability of a firm is negatively associated with the energy-cost intensity.

A theoretically ambiguous relationship between digital investment and energy-cost intensity is detected: on one hand, digital systems can contribute to monitoring and optimisation, but on the other hand, energy-cost pressure can reduce the complementary investment required for triggering digital returns and the literature does not provide a clear indication of the direction of the relationship.

RQ1: Does the digital investment intensity-firm profitability relationship differ across low and high energy-cost intensity firms?

The asset turnover ratio (sales/total assets) measures the amount of revenue generated per dollar of assets. It doesn't directly measure pressure on capacity or disruption to implementation, but it could be a reflection of asset utilisation, operating intensity, sectoral capital structure, or asset-light business models. It was hypothesized that there would be a positive relationship with ROA, and no directionality was predicted for the relationship of ROA with digital investment.

H7: A higher asset turnover is related to higher firm profitability.

RQ2: How does asset turnover moderate the relation between digital-investment intensity and the firm's profitability?

2.6 Profitability persistence

Profitability is likely to stick around in the long term but should mean revert in the short term. Positive but incomplete persistence was documented by Mueller [31, 32], McGahan and Porter [33], Fama and French [34] and Gschwandtner [35] and was confirmed by Hirsch [36] who showed that estimates of persistence vary with method and sample design; this is consistent with the view that persistence is a dynamic phenomenon, but does not imply that this study discovers the mechanism through which persistence operates.

H8: Past profitability and current profitability will have positive correlation.

3. Data and Methodology

3.1 Data and sample

Firm level data was obtained from CMIE Prowess for annual data for Indian manufacturing firms, for the period 2014-2024. The original extraction yielded 71,742 firm-year observations; after the removal of 29,745 observations due to missing core variables and 4 observations due to negative values (that were invalid), a contemporaneous sample of 41,993 observations from 5,288 firms remained. This was reduced to 35,236 observations by 5,050 firms after requiring a valid lagged ROA. The remaining history data resulted in 34,383 observations from 4,476 firms prior to transformation and 29,158 observations from 4,475 firms following first differencing. Finally, the restriction of at least four consecutive usable dynamic observations per firm yielded the 28,304 observations from 4,049 firms that were subsequently used for the main results. Further history requirements produced 34,383 observations from 4,476 firms before transformation and 29,158 from 4,475 firms after first differencing. A final restriction — at least four consecutive usable dynamic observations per firm — produced the 28,304 observations from 4,049 firms used for the principal results.

Table 1: Sample construction

Sample stage	**Firm-year observations**	**Firms**	**Period**
Initial manufacturing dataset	71,742	—	2014–2024
Observations removed: missing core variables	29,745	—	—
Observations removed: invalid negative values	4	—	—
Final contemporaneous analytical sample	41,993	5,288	2014–2024
Dynamic sample requiring ROA(t−1)	35,236	5,050	2015–2024
GMM sample, ≥3 usable observations	34,383	4,476	2015–2024
Difference-GMM estimation sample	29,158	4,475	Effective transformed sample
Consecutive-history GMM sample	28,304	4,049	Effective transformed sample

Note: The final sample required non-missing values for profit after tax, total assets, software and IT expenditure, sales, net working capital, employee expenditure, energy expenditure, net fixed assets and debt. Total assets and sales were required to be positive; software and IT expenditure, employee expenditure, energy expenditure, net fixed assets and debt were required to be non-negative. Continuous ratio variables were winsorised at the 1st and 99th percentiles.

This consecutive-history rule is stricter than strictly necessary for the broader dynamic sample, but it ensures every retained firm contributes at least three transformed observations to the GMM estimation, without changing any variable definition or the period the source data cover — only the estimation sample. Descriptive statistics and correlations are accordingly reported for the larger dynamic sample, while the GMM coefficients come from the stricter consecutive-history sample.

3.2 Variables and data treatment

ROA is profit after tax over total assets, and digital-investment intensity (DIT) is software and IT expenditure over sales. The remaining variables follow the same ratio logic: financial slack is net working capital over total assets; workforce intensity is employee expenditure over sales; energy-cost intensity is energy expenditure over sales; firm size is the natural log of total assets; tangibility is net fixed assets over total assets; leverage is debt over total assets; and asset turnover is sales over total assets. All interaction terms use mean-centred constituent variables.

Table 2: Variable definitions

Variable	**Operational definition**	**Role**
Return on assets (ROA)	Profit after tax / total assets	Dependent variable
Lagged ROA	ROA(i,t−1)	Dynamic persistence
Digital-investment intensity (DIT)	Software and IT expenditure / sales	Main explanatory variable
Financial slack	Net working capital / total assets	Organisational resource
Workforce intensity	Employee expenditure / sales	Organisational resource

Variable	Operational definition	Role
Energy-cost intensity	Energy expenditure / sales	Operating-resource measure
Firm size	Natural logarithm of total assets	Control
Tangibility	Net fixed assets / total assets	Control
Leverage	Debt / total assets	Control
Asset turnover	Sales / total assets	Control
DIT × Slack	Mean-centred DIT × mean-centred financial slack	Moderation
DIT × Workforce	Mean-centred DIT × mean-centred workforce intensity	Moderation
DIT × Energy	Mean-centred DIT × mean-centred energy intensity	Moderation
DIT × Asset turnover	Mean-centred DIT × mean-centred asset turnover	Moderation

Note: Continuous ratio variables were winsorised at the 1st and 99th percentiles; firm size was not winsorised.

3.3 Model and estimation strategy

The baseline dynamic model took the form:

$$ROA_{it} = \alpha ROA_{i,t-1} + \beta DIT_{it} + \gamma' X_{it} + \eta_i + \lambda_t + \varepsilon_{it} \quad (1)$$

where X denotes the vector of controls, ηi captures time-invariant firm heterogeneity, and λt denotes year effects. Interaction models added a DIT × M term and the corresponding constituent variables, where M was financial slack, workforce intensity, energy-cost intensity, or asset turnover in turn. Mean-centring set the DIT coefficient equal to the conditional association at the moderator's mean without altering the interaction coefficient itself [37, 38].

In a short dynamic panel, the within transformation ties the transformed lagged dependent variable to the transformed disturbance, biasing the within-groups estimator [39] — the large gap between the pooled-OLS and fixed-effects persistence estimates reported below reflects exactly that. Difference GMM strips out firm effects by first-differencing and instruments the resulting endogenous differenced variables with suitably lagged levels [40]; ROA and DIT were both treated as GMM-style variables. System GMM was also tried, but its extra level-equation moment conditions were rejected, so it was not carried forward.

Two-step difference GMM with Windmeijer-corrected robust standard errors [41] became the preferred estimator on that basis. To keep instrument proliferation in check, the instrument matrix was collapsed and restricted to lags two and three [42]. This left 20 instruments in the base model estimated on 4,049 firms, 22 in each standalone interaction model, and 24 in the combined slack–workforce specification, with year effects included throughout.

The Arellano–Bond AR(1) and AR(2) tests were performed to check for serial correlation in the differenced residuals: AR(1) is expected to be significant by construction, whereas AR(2) is expected not to be significant to validate the maintained moment conditions. Hansen and Sargan tests then assessed the overidentifying restrictions, though non-rejection is evidence for validity rather than proof of it. Dynamic pooled OLS and dynamic fixed effects with firm-clustered standard errors served as benchmarks; because the fixed-effects residuals proved cross-sectionally dependent, an additional FE specification with Driscoll–Kraay standard errors [43] supplied inference robust to that dependence.

No single estimator carries the full weight of the argument here. Pooled OLS leaves unobserved firm heterogeneity in the error term; the within estimator removes that heterogeneity but picks up bias of its own in a short panel; FE–DK changes only the standard errors, not the FE point estimates, to account for the detected error dependence. Difference GMM does the principal work of the analysis, while the other three specifications show whether the signs and significance of the results survive different treatments of firm effects and the error structure.

Short-run marginal effects of DIT were evaluated at the moderator's mean and at one standard deviation above and below it. Dividing the short-run association by one minus the relevant persistence coefficient gives an approximate long-run figure — a descriptive transformation with no standard error or significance test attached.

4. Empirical Results

4.1 Descriptive evidence and diagnostics

Table 3 reports descriptive statistics for the dynamic sample of 35,236 observations. Mean ROA was 0.0374 (SD = 0.0783). Mean DIT was 0.00188, equivalent to approximately 0.19 per cent of sales, with a median of 0.000758 and an SD of 0.00356. Mean financial slack was 0.1317, workforce intensity 0.0933, energy-cost intensity 0.0419, and asset turnover 1.4350.

Table 3: Descriptive statistics

Variable	Mean	SD	Median	Minimum	Maximum
ROA	0.0374	0.0783	0.0348	−0.3037	0.2530
Digital investment / sales	0.00188	0.00356	0.000758	0.000029	0.02521
Financial slack	0.1317	0.2308	0.1336	−0.7840	0.6654
Workforce expenditure / sales	0.0933	0.0840	0.0709	0.00349	0.5011
Energy expenditure / sales	0.0419	0.0536	0.0222	0.000228	0.3058
Firm size	7.5005	1.4969	7.4274	1.5686	15.3945
Tangibility	0.2979	0.1712	0.2783	0.0160	0.7627
Leverage	0.3243	0.2449	0.2967	0.0010	1.3672
Asset turnover	1.4350	1.0190	1.1924	0.1062	6.2326

Note: Dynamic estimation sample (N = 35,236). All ratio variables are winsorised at the 1st and 99th percentiles. Firm size is not winsorised.

The correlation matrix in Table 4 showed that ROA was negatively correlated with DIT (−0.153), workforce intensity (−0.217), energy-cost intensity (−0.155), and leverage (−0.484), and positively correlated with financial slack (0.453) and asset turnover (0.175); all coefficients were significant at 1 per cent. These bivariate associations are descriptive only. The maximum absolute pairwise correlation was approximately 0.484, and a mean VIF of 1.71 (maximum substantive-variable VIF of 1.70) indicated no serious multicollinearity.

Table 4: Pearson correlation matrix

Variable	1	2	3	4	5	6	7	8	9
1. ROA	1.000								
2. Digital investment	−0.153***	1.000							
3. Financial slack	0.453***	−0.054***	1.000						
4. Workforce intensity	−0.217***	0.426***	−0.121***	1.000					
5. Energy intensity	−0.155***	−0.034***	−0.206***	0.097***	1.000				
6. Firm size	0.128***	−0.029***	−0.011**	−0.125***	−0.022***	1.000			
7. Tangibility	−0.156***	−0.002	−0.430***	0.106***	0.362***	0.035***	1.000		
8. Leverage	−0.484***	−0.011**	−0.483***	−0.006	0.173***	−0.135***	0.204***	1.000	

Variable	1	2	3	4	5	6	7	8	9
9. Asset turnover	0.175***	−0.213***	0.127***	−0.406***	−0.141***	−0.200***	−0.198***	−0.009	1.000

Note: N = 35,236. *$p < 0.10$, $p < 0.05$,* ** $p < 0.01$. The maximum absolute pairwise correlation is approximately 0.484; the mean VIF is 1.71, indicating no serious multicollinearity.

The Modified Wald test rejected the null of groupwise homoskedasticity (p = 0.000), the Wooldridge test detected first-order within-firm serial correlation (F(1, 4719) = 332.930, p = 0.000), and the Pesaran CD test indicated cross-sectional dependence (CD = 30.98, p = 0.000), motivating clustered and Driscoll–Kraay inference for the fixed-effects benchmarks.

Table 5: Pre-estimation and panel diagnostics

Diagnostic test	Null hypothesis	Test statistic	p-value	Implication
Modified Wald test for groupwise heteroskedasticity	Homoskedastic errors across firms	$\chi^2(5050)$ = 39,106,044.30	0.000	Strong groupwise heteroskedasticity is present
Wooldridge test for first-order serial correlation	No first-order autocorrelation	F(1, 4719) = 332.930	0.000	Strong within-firm serial correlation is present
Pesaran CD test	Weak cross-sectional dependence	CD = 30.98	0.000	Strong residual cross-sectional dependence is present
Mean VIF	No harmful multicollinearity	1.71	—	Regressors are not severely collinear
Maximum substantive-variable VIF	No harmful multicollinearity	1.70	—	No variable requires exclusion

Note: Diagnostics apply to the fixed-effects specification and complement, but do not replace, the AR(1)/AR(2) and Hansen/Sargan diagnostics reported for the GMM models in Tables 6 and 7.

4.2 Base dynamic estimates

The pooled-OLS DIT coefficient was −0.6343 (SE = 0.1474, p < 0.01), while the FE and FE–DK coefficient was −0.0930, which was not significant. However, in the GMM model, DIT was not significantly different from zero (−2.4998 (SE = 1.8998)), and so the hypothesis that H1 was not supported.

Financial slack was positively associated with ROA (0.1045, SE = 0.0086, p < 0.01), supporting H2. As would be predicted based on non-directional H4, workforce intensity was negatively related to ROA (−0.3259, SE = 0.0431, p < 0.01). However, the energy-cost intensity was not significant (0.0065, SE = 0.0457) and thus H6 was not confirmed. Asset turnover was positively associated with ROA (0.0217, SE = 0.0020, p < 0.01), supporting H7. The other controls that were included were firm size (positive) and tangibility and leverage (negative and significant). The fact that these control estimates were significant for the interpretation of the digital coefficient conditionally was important to ensure that the broad differences in scale, asset composition, indebtedness, and revenue generation of different firms were not simply explained by the DIT estimate. The estimated model with 20 instruments met the model diagnosis (AR(1) significant at 0.000 level, AR(2) insignificant at 0.570 level, null hypothesis for the Hansen test was not rejected at 0.683 level, null hypothesis for the Sargan test was not rejected at 0.319 level).

The model estimated with 20 instruments, satisfied its diagnostic requirements: AR(1) was significant (p = 0.000), AR(2) was not (p = 0.570), and neither the Hansen (p = 0.683) nor the Sargan (p = 0.319) test rejected its null hypothesis.

Table 6: Base dynamic models of profitability

Variables	Dynamic pooled OLS	Dynamic FE	Dynamic FE–DK	Difference GMM
ROA(t−1)	0.5052*** (0.0114)	0.1631*** (0.0134)	0.1631** (0.0523)	0.3768*** (0.0208)
Digital investment	−0.6343*** (0.1474)	−0.0930 (0.3430)	−0.0930 (0.3031)	−2.4998 (1.8998)

Variables	Dynamic pooled OLS	Dynamic FE	Dynamic FE–DK	Difference GMM
Financial slack	0.0473*** (0.0030)	0.0735*** (0.0055)	0.0735*** (0.0083)	0.1045*** (0.0086)
Workforce intensity	−0.0664*** (0.0066)	−0.2797*** (0.0212)	−0.2797*** (0.0195)	−0.3259*** (0.0431)
Energy intensity	−0.0441*** (0.0079)	0.0238 (0.0313)	0.0238 (0.0179)	0.0065 (0.0457)
Firm size	0.0018*** (0.0003)	0.0083*** (0.0022)	0.0083** (0.0032)	0.0305*** (0.0033)
Tangibility	0.0230*** (0.0028)	−0.0117* (0.0063)	−0.0117* (0.0063)	−0.0191** (0.0085)
Leverage	−0.0565*** (0.0025)	−0.0913*** (0.0056)	−0.0913*** (0.0096)	−0.1141*** (0.0083)
Asset turnover	0.0049*** (0.0004)	0.0219*** (0.0014)	0.0219*** (0.0013)	0.0217*** (0.0020)
Firm effects	No	Yes	Yes	Eliminated by differencing
Year effects	Yes	Yes	Yes	Yes
Firm-clustered SE	Yes	Yes	No	No
Driscoll–Kraay SE	No	No	Yes	No
Windmeijer-corrected robust SE	No	No	No	Yes
Observations	35,236	35,236	35,236	28,304
Firms	5,050	5,050	5,050	4,049
R^2	0.5210	Within: 0.2750	Within: 0.2750	Not applicable
F-statistic	706.85***	188.32***	274.56***	131.17***
Instruments	—	—	—	20
AR(1), p-value	—	—	—	0.000
AR(2), p-value	—	—	—	0.570
Hansen, p-value	—	—	—	0.683
Sargan, p-value	—	—	—	0.319
Instrument lag window	—	—	—	2–3
Collapsed instruments	—	—	—	Yes
Model status	Benchmark	Benchmark	Robustness	Principal dynamic estimator

Note: Standard errors in parentheses. *p < 0.10, p < 0.05,* ** p < 0.01. The Difference-GMM model uses two-step estimation with Windmeijer-corrected robust standard errors; ROA and digital investment are treated as GMM-style variables; instruments are collapsed and restricted to lags 2–3. System-GMM specifications were rejected because the Hansen and Difference-in-Hansen tests rejected the additional level-equation moment conditions.

4.3 Interaction and marginal-effect estimate

The workforce model yielded a DIT coefficient of −4.8798 (SE = 2.0070, $p < 0.05$) at mean workforce intensity and a positive interaction of 18.7694 (SE = 9.3258, $p < 0.05$); in the combined model this interaction remained positive at 16.3977 (SE = 9.0246, $p < 0.10$), weaker evidence of the same pattern. H5 was supported in the standalone model, with the conditional DIT association becoming less negative as workforce intensity rose.

The asset-turnover model yielded a DIT coefficient of −6.3184 (SE = 2.2201, $p < 0.01$) at mean asset turnover and an interaction of −5.3478 (SE = 1.7668, $p < 0.01$), so RQ2 was answered by a statistically significant negative conditioning relationship. The DIT × energy-cost interaction was positive but insignificant (22.6729, SE = 16.3162), providing no statistically significant moderation evidence for RQ1.

Across the interaction models, diagnostics remained acceptable: AR(1) equalled 0.000 throughout, AR(2) p-values ranged from 0.430 to 0.548, and neither the Hansen nor the Sargan test rejected its null hypothesis at 5 per cent.

Table 7: Difference-GMM interaction models

Variables	DIT × Slack	DIT × Workforce	DIT × Asset turnover	DIT × Energy	Combined
ROA(t−1)	0.3761*** (0.0208)	0.3707*** (0.0208)	0.3658*** (0.0204)	0.3717*** (0.0207)	0.3709*** (0.0209)
Digital investment	−3.5834* (1.9082)	−4.8798** (2.0070)	−6.3184*** (2.2201)	−2.8638 (1.8220)	−5.4207** (2.1070)
Financial slack	0.1064*** (0.0091)	0.1043*** (0.0086)	0.1036*** (0.0088)	0.1042*** (0.0086)	0.1055*** (0.0090)
Workforce intensity	−0.3229*** (0.0432)	−0.4025*** (0.0662)	−0.3790*** (0.0522)	−0.3475*** (0.0484)	−0.3879*** (0.0636)
Energy intensity	0.0018 (0.0470)	−0.0349 (0.0493)	−0.0184 (0.0462)	−0.0623 (0.0684)	−0.0330 (0.0497)
Asset turnover	0.0212*** (0.0020)	0.0192*** (0.0023)	0.0136*** (0.0035)	0.0205*** (0.0022)	0.0192*** (0.0023)
DIT × Slack	−2.6750 (3.8832)	—	—	—	−1.8770 (3.7344)
DIT × Workforce	—	18.7694** (9.3258)	—	—	16.3977* (9.0246)
DIT × Asset turnover	—	—	−5.3478*** (1.7668)	—	—
DIT × Energy	—	—	—	22.6729 (16.3162)	—
Firm size	0.0304***	0.0277***	0.0256***	0.0294***	0.0280***
Tangibility	−0.0176**	−0.0165*	−0.0168**	−0.0160*	−0.0160*
Leverage	−0.1149***	−0.1145***	−0.1131***	−0.1135***	−0.1153***
Year effects	Yes	Yes	Yes	Yes	Yes
Firm effects	Eliminated	Eliminated	Eliminated	Eliminated	Eliminated
Observations	28,304	28,304	28,304	28,304	28,304
Firms	4,049	4,049	4,049	4,049	4,049
Instruments	22	22	22	22	24
F-statistic	128.18***	122.96***	120.57***	124.58***	119.63***
AR(1), p-value	0.000	0.000	0.000	0.000	0.000
AR(2), p-value	0.577	0.534	0.430	0.536	0.548
Hansen, p-value	0.670	0.800	0.366	0.899	0.730
Sargan, p-value	0.098	0.371	0.167	0.659	0.104
Instrument lag window	2–3	2–3	2–3	2–3	2–3
Collapsed instruments	Yes	Yes	Yes	Yes	Yes

Note: Standard errors in parentheses. $p < 0.10$, $p < 0.05$, ** $p < 0.01$. All models use two-step difference GMM with Windmeijer-corrected robust standard errors. Digital investment and its interaction term are treated as GMM-style variables; constituent variables are mean-centred.

These interaction results also caution against treating the insignificant base coefficient as the complete digital-investment result. Once moderators were centred, the DIT constituent coefficient referred to a firm at the moderator's mean, while the interaction term captured how that conditional association changed with the moderator. The significant workforce and asset-turnover interactions therefore revealed structured heterogeneity despite the insignificant average direct coefficient, while the insignificant slack and energy interactions showed that conditionality was not mechanically generated by adding any plausible moderator.

Table 8 reports the conditional short-run marginal effects. In the workforce model, the DIT association was −6.432 one SD below the mean, −4.880 at the mean, and −3.328 one SD above the mean, becoming less negative but remaining negative throughout this range; the point-estimate zero crossing occurred at a centred workforce intensity of approximately 0.260, more than three SD above the sample mean. The asset turnover model's corresponding values were: −0.912, −6.318, and −11.725, further and further into the negative as the asset turnover increased.

Table 8: The marginal effects of digital investment

Panel A. Short-run effect of digital investment at workforce-intensity values.		
Workforce intensity	Centred value	Marginal effect of DIT
Low: mean − 1 SD	−0.08270	−6.432
Mean	0	−4.880
High: mean + 1 SD	0.08270	−3.328
Panel B. Short-run effect of digital investment at asset-turnover values.		
Asset turnover	Centred value	Marginal effect of DIT
Low: mean − 1 SD	−1.01093	−0.912
Mean	0	−6.318
High: mean + 1 SD	1.01093	−11.725
Panel C. Approximate long-run marginal effects		
Workforce intensity	Approximate long-run DIT effect	
Mean − 1 SD	−10.22	
Mean	−7.75	
Mean + 1 SD	−5.29	
Asset turnover	Approximate long-run DIT effect	
Mean − 1 SD	−1.44	
Mean	−9.96	
Mean + 1 SD	−18.49	

5. Discussion

The lagged-ROA coefficient is positive, significant and comfortably below unity, indicating some persistence as the literature has documented this frequently [31–36]. Several possibilities exist, such as adjustments to resources that are specific to the firm, positioning in the competition, or adjustment frictions.

The base model did not provide statistically significant evidence of a separate association between DIT and ROA. That's distinct from — not contrary to — studies that found positive digital-transformation relationships, as most of those studies are based on text indices, patents or capabilities measures instead of actual spending. It complies with the older distinction between productivity and profitability, and the wider perspective that the value of IT is shaped by organisational complements and timing [6, 7, 13]. A negative IT-investment association has been reported by Guan and Wang [5] in manufacturing in China, but this should be interpreted with caution as the present coefficient never became significant and the two settings are quite different.

A positive coefficient was the most important indicator of conditionality, as a positive relationship between DIT and ROA was found for growing values of the worker-expenditure intensity, in line with the complementarity arguments developed around the emphasis on workplace organisation, higher-order skills and digital skills [16–19, 27].The comparison can only be indirect since workforce intensity is an accounting ratio, not a window into skills, training, or organisational capability and its own direct coefficient was negative. Higher labour expenditure is not in itself good for profitability The same variable negatively impacted ROA directly, and reduced the conditional impact of digital spending.

The results for asset turnover were the inverse: positive direct relationship with ROA and a negative interaction with DIT.That answers RQ2 without explaining why higher sales-to-assets ratios worsen the digital-investment relationship — intensive asset use, sector composition, asset-light models, and thinner implementation buffers are plausible but untested stories, and the finding is a reminder that a favourable direct operating association carries no guarantee of positive digital complementarity.

Financial slack helped profitability directly without moving the DIT relationship — in line with the resource-buffer tradition [21] and with evidence elsewhere that slack–performance links depend on measurement and context [22–26]. A working-capital-heavy slack ratio may support general liquidity without being the funds a firm actually earmarks for digital projects; the direct profitability role of slack and its unconfirmed role as a digital enabler are, on this evidence, two separate things.

Energy-cost intensity sat out both roles — insignificant directly and as a moderator, parting ways with Alavani et al. [28], whose PAT-covered Indian sample turned up a negative energy-intensity association under a different sample and treatment. Sectoral heterogeneity in energy technology, price pass-through, and energy expenditure's dual role as cost and production-scale proxy could all be pulling the pooled relationship toward zero — plausible, but untested.

Taken together, the results favoured a selective contingency interpretation over a uniformly positive or negative account of digital expenditure. Workforce intensity mitigated; asset turnover intensified; financial slack helped directly without moderating; energy-cost intensity mattered in neither respect. Complementarity, in short, was resource-specific rather than universal, and direct and interactive coefficients answered different questions about each variable's role.

6. Theoretical Implications

Four theoretical points follow from this pattern of results. A single direct coefficient cannot capture digital-investment value: an insignificant base-model association alongside significant interaction effects fits a benefit-realisation account in which accounting outcomes hinge on organisational and operating context [6, 9], even though adjustment costs and delayed returns were never measured directly.

Complementarity, moreover, proved selective rather than automatic, matching the conditional logic Milgrom and Roberts [15] set out. A positive workforce interaction sat next to insignificant slack and energy interactions and a negative asset-turnover interaction — reason enough not to assume any co-present organisational resource will complement digital expenditure.

Direct and interactive roles pulled apart for several variables. Workforce intensity hurt profitability directly while helping the DIT relationship; asset turnover helped profitability directly while hurting the DIT relationship; financial slack helped directly and did neither in a moderating sense. Resource theories drawing on this literature need to keep a variable's independent association separate from its role in conditioning another one — a distinction already implicit in the complementarity and IT-business-value frameworks reviewed in Section 2 [13, 15].

And digital expenditure is not digital capability: annual software and IT spending records a commitment of resources, not assimilation, accumulated capability, or a completed transformation [13, 17, 18, 20] — a distinction that helps reconcile these findings with capability-based studies reporting rosier outcomes.

7. Managerial Implications

Managers should not expect an automatic short-run profitability premium from digital spending, since the estimates give no support for one — though digital investment may still hold operational or longer-horizon value, consistent with a benefit-realisation view under which accounting returns to IT expenditure can be delayed or conditional [6, 9].

The workforce and digital expenditure interaction raises a question: Do digital projects have real process ownership, process implementation support and process organisation support? This matches the complementarity claim, which is based on the context of the work place [16, 17]. However, this accounting approach does not allow to identify those mechanisms and does not give a licence to simply increase labour costs as a quick way to improve digital pay-off.

Companies with a high sales-to-asset ratio might want to plan carefully and manage any asset turnover-related disruption with extra sensitivity, as the conditional association between these variables deteriorated at higher asset turnover levels; asset turnover is not a measure of capacity stress, so it should be interpreted as a planning caution rather than a causal prescription.

Nor should the financial slack be taken to mean that there are no digital returns. The relationship between the working-capital position and profitability was consistent with slack's long-cited moderating effect [21] and was statistically significant, although the interaction between the working-capital position and the DIT never became significant. All of this is based on observations, not causality.

8. Limitations and Future Research

The expenditure measure used here says nothing about project quality, implementation stage, cloud contracts booked The measure of expenditure used here does not indicate anything about the quality of projects delivered, the stage of project implementation, cloud contracts secured in other projects or outsourcing of digital services, nor about the investment of IT capital and capability. Future work could be broken down into the following components based on data: Hardware, Software, Automation, Analytics, Cybersecurity, and AI-related.

Workforce intensity is a cost ratio and does not provide an indication of skills, training, occupational mix or digital competence — there is a need for more rigorous tests of organisational complementarity using accounting data alongside workforce or survey data. Net working capital also over total assets is one manifestation of financial slack; unutilized debt capacity, cash holdings, and absorbed slack are all other manifestations.

The measure of asset turnover may mask true efficiencies and operating intensity, or sector-specific technology or plant-level throughput and fixed-asset utilisation or inventory data may help identify the negative interaction found here. It is important to note that the relationship between energy and manufacturing may not become apparent until considered within a more limited set of manufacturing sub-sectors.

The endogeneity problem mentioned in Section 3 is tackled by Difference GMM, provided that its assumptions are satisfied, but internal instruments are difficult to come up with and diagnostics which do not reject validity do not establish validity. The results of these companies from the listed manufacturing group may not cross over to services, unlisted companies, other countries, or other regulatory periods. Last, the marginal effects in Section 4 lack independent standard errors, which may be estimated in the future with a gap delta method or a bootstrap procedure.

9. Conclusion

The purpose of this study was to investigate digital-investment intensity and dynamic profitability of Indian manufacturing firms using CMIE Prowess data for 2014–2024 and estimating two-step difference GMM with restricted, collapsed instruments, dynamic pooled OLS, dynamic fixed-effects and Driscoll–Kraay benchmarks.

The profitability premium that arises as a result of digital-investment intensity did not emerge in the base model, despite the fact that profitability was found to be positively persistent. Workforce intensity had both sides of its relationship with ROA negative and positive; asset turnover had both sides of its relationship with ROA negative and positive; both were tested negative directly and positive in conditioning the negative direct relationship. Financial slack also positively affected profitability with no influence on the positive relationship between digital investment; nor did energy cost intensity have an effect on either of those factors.

The bigger question is that digital spending is not a standalone project but is part of an organisation's context, and the profit association of it is not always the same: a resource advantage does not always lead to a digital complementarity, and annual spending doesn't mean digital capability. The result is a contextually rich description of digital investment in Indian manufacturing, which doesn't attempt to explain the underlying causal processes and the long-term futures of these investments but leaves it for others to study.

Data Availability Statement

The data was extracted from proprietary CMIE Prowess database and access may be obtained directly through CMIE.

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