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INDIA'S DRUGS AND PHARMACEUTICAL INDUSTRY FROM AN INTELLECTUAL CAPITAL LENS: A DYNAMIC PANEL PERFORMANCE ANALYSIS

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ABSTRACT
India's pharmaceutical and drug companies transform scientific knowledge, organizational processes, external networks and physical resources into commercially feasible products at the end of lengthy development cycles and during times of rigorous regulation, but the profitability of this knowledge base has yet to be explored in a dynamic panel setting. This study aims to know whether the Modified Value-Added Intellectual Coefficient (CVaic) and its factors are correlated to the profitability of Indian listed pharmaceutical companies after adjusting for persistence, leverage, tangibility and size. The study estimates pooled OLS, fixed-effects and two-step system GMM models using data from CMIE Prowess for 267 firms (2,062 firm-year observations, 2014-2024). The persistence estimates generated by the GMM procedure fall between the pooled OLS and fixed-effects persistence estimates, with all three estimates being positive and significant throughout. All the GMM estimators have a positive relationship between aggregate MVAIC and ROA. The component models show that there is heterogeneity, with positive relationships between structural and capital employed efficiency and profitability and a slightly positive relationship between human capital efficiency and profitability, while the relationship between relational capital efficiency and profitability is negative and significant. Leverage is negative and strong all the way through. The returns on intellectual capital are not necessarily related to total investment, but to producing value from the investment.

KEYWORDS: Intellectual capital; MVAIC; pharmaceutical industry; profitability; system GMM; India

1. INTRODUCTION
India's pharmaceutical sector is among the largest in the world by volume and supplies a substantial share of generic medicines and vaccines to both domestic and export markets, giving the sector's financial performance a significance that extends beyond shareholder returns to public-health capacity and industrial policy. This scale, however, sits alongside considerable heterogeneity: the listed universe spans large, diversified, research-intensive firms and smaller, more narrowly focused manufacturers, and profitability studies of the sector have accordingly produced mixed conclusions depending on the sample, time period and methodology used. The regulatory environment adds a further layer of complexity specific to this industry. Mahor and Banerji (2023), studying the dynamic profitability determinants of Indian pharmaceutical firms using cointegration methods, find that working-capital intensity, R&D intensity and physical-capital intensity all carry statistically distinct short- and long-run relationships with ROA, reinforcing the case for a dynamic rather than static empirical treatment of profitability in this industry. The present study extends that dynamic orientation specifically to intellectual-capital efficiency.
India's drugs and pharmaceuticals sector occupies an unusual position among emerging-market industries: it is capital intensive and tightly regulated, yet its competitive edge rests on scientific and organisational knowledge that accumulates over long product-development cycles (Nandy, 2022). Firms in this sector do not compete on plant and financial capital alone; they compete on the maturity of their regulatory and quality-assurance systems and the strength of their commercial and distribution relationships. Conventional financial-statement analysis, anchored in tangible assets and reported expenditure, captures only part of this resource base. The stock of human expertise, codified organisational routines, and external relationships that support the conversion of physical and financial resources into profit does not appear on the balance sheet, yet it is widely argued to shape how efficiently a firm converts its resources into returns (Bontis, 1998)- a stock generally labelled Intellectual Capital.
Two features of the industry complicate a straightforward accounting test of this idea. First, pharmaceutical profitability tends to be persistent: a firm's competitive position carries from year to year through regulatory approvals,

distribution networks and reputation, so a static or cross-sectional model risks attributing this persistence to whichever regressor happens to correlate with it. Second, intellectual-capital related spending (R&D, employee development, marketing) and profitability are plausibly determined jointly- a profitable firm can afford to invest further in these activities, which may raise measured efficiency in the following period (Gupta et al., 2022). Both features point toward a dynamic panel design with explicit attention to endogeneity, rather than a static specification.

Recent Indian evidence reinforces why this matters now. Singhania and Panda (2025) show that intellectual-capital disclosure is becoming a materially more prominent feature of Indian corporate reporting as firms respond to Industry 4.0-era competitive pressure, and Prasad and Mondal (2025) demonstrate, using GMM estimation on Indian listed SMEs, that intellectual capital's relationship with performance is sensitive to the dynamic specification chosen- a methodological finding directly relevant to how MVAIC-profitability studies should be modelled. Within the pharmaceutical sector itself, Mahor and Banerji (2023) find that Indian pharmaceutical profitability depends dynamically on working-capital, R&D and physical-capital intensity, underscoring that profitability determinants in this industry are better modelled as an evolving, firm-specific process than as a static cross-section- a finding this study builds on directly. Yet dynamic-panel evidence that isolates intellectual-capital efficiency specifically, net of this persistence, remains scarce for the sector.

Research gap. Existing MVAIC/VAIC evidence spans banking and financial services (Ayinaddis et al., 2024), manufacturing (Xu & Li, 2022), and- closest to the present setting- Indian pharmaceuticals (Gupta et al., 2022; Festa et al., 2020), but this pharmaceutical-sector evidence rests largely on static specifications that do not separate profitability persistence from the marginal contribution of intellectual-capital efficiency, and rarely subject the aggregate MVAIC score to a component-level decomposition capable of detecting offsetting effects. This leaves two open questions: whether the aggregate MVAIC-profitability association survives a dynamic, endogeneity-robust specification, and whether that aggregate association is uniform across its four components or conceals components that pull in opposite directions.

This study addresses that gap by estimating a persistence-augmented dynamic model of returns on assets (ROA) for Indian listed drugs and pharmaceutical companies, using the Modified Value-Added Intellectual Coefficient as the efficiency measure of interest. MVAIC decomposes value-added efficiency into four components, measuring the efficiencies of human, structural and relational capitals, and the capital employed - enabling analysis beyond a single aggregate score to identify which resource-deployment channels actually drive profitability (Pulic, 2000; Nazari & Herremans, 2007). The empirical strategy uses pooled OLS and fixed effects as conventional upper and lower bounds on the true persistence parameter, and two-step system GMM as the preferred estimator, since GMM addresses both the Nickell bias present in dynamic fixed-effects estimation (Nickell, 1981) and the potential endogeneity of MVAIC and leverage with respect to profitability.

Aim and contribution. The study aims to analysis the association of intellectual-capital efficiency with profitability in Indian listed pharmaceutical firms once profitability persistence and endogeneity are properly modelled, and to identify which components of that efficiency carry the association. Its contribution is threefold: it isolates intellectual-capital efficiency from traditional financial and physical capital using a dynamic panel framework rather than a static one; it addresses simultaneity and dynamic endogeneity through system GMM rather than OLS/fixed-effects alone; and it shows that the MVAIC-profitability relationship is not uniform- relational capital efficiency (marketing expenditure relative to value added) is negatively, not positively, associated with profitability, which qualifies the common “more intellectual capital is better” reading of MVAIC results and has direct relevance for how pharmaceutical firms and regulators interpret commercial-spending disclosures.

The article is structured as follows. Section 2 presents the review of literature, theoretical framework, and states the hypotheses and research questions. Section 3 describes the sample data, variable construction and methodology. Section 4 reports the aggregate and component-level results, and Section 5 has the discussion for these. Section 6 presents implications together with limitations, and Section 7 has the conclusion.

2. LITERATURE REVIEW AND THEORETICAL FRAMEWORK

2.1 Intellectual Capital Measurement

According to Bontis (1998), there are three types of intellectual capital: 1) human capital including employees’ knowledge, skills and competencies, 2) structural capital including the system, process or infrastructure that remain in place beyond the time of any employee, and 3) relational capital including the relationships with customers, suppliers and business partners. Building on this taxonomy, Pulic (2000) developed the Value-Added Intellectual Coefficient (VAIC™), decomposing value creation into Human capital efficiency, structural-capital efficiency and capital employed efficiency; Nazari and Herremans (2007) extended the model with a relational-capital efficiency component (marketing expenditure relative to value added) to better approximate Bontis's tripartite structure. VAIC/MVAIC has been applied widely. Gupta and Raman (2020), for instance, identify intellectual-capital efficiency as a determinant of operational efficiency among Indian firms- but it has also drawn sustained methodological scrutiny: because its components are built from accounting aggregates, they capture the efficiency of the accounting inputs chosen rather than the depth, uniqueness or strategic significance of the underlying intangible resource (Ståhle et al., 2011). MVAIC should therefore be read as an efficiency-of-conversion measure for a defined set of accounting resources- employee expenditure, structural capital, marketing expenditure and capital employed- and not as a comprehensive measure of a firm's intangible resource stock. This distinction between accounting proxy and underlying construct runs through the interpretation offered later in this paper.

2.2 Pharmaceutical Firms as Knowledge-Intensive Organisations

Pharmaceuticals is a paradigmatic knowledge industry: specialised scientific expertise, R&D capability, regulatory know-how and commercialisation infrastructure are all first-order competitive assets. Nandy (2022), studying 12 NSE-listed Indian pharmaceutical firms, finds R&D expenditure positively related to ROA, return on equity and market capitalisation. Returns to knowledge investment are not, however, immediate: Shivdas and Ray (2021) find R&D and regulatory spending associated with negative short-run profitability in Indian pharmaceutical firms, consistent with the long gestation period between drug discovery and regulatory approval- a time-lag that resurfaces in Section 2.7 in relation to relational-capital efficiency specifically. Comparable lag structures have been documented outside India where studies show that R&D investment in Chinese pharmaceutical firms interacts with debt capital and ownership concentration with delayed effects on performance (Su et al., 2021), and pharmaceutical R&D intensity constrains short-run financial flexibility even where it strengthens longer-run bargaining power (Tömöri et al., 2022). Mathur et al. (2021), examining capital structure and competitive intensity in Indian pharmaceutical companies, similarly report that the industry's financing and competitive dynamics interact with performance in ways that a purely static model would miss, reinforcing the sector-specific case for dynamic estimation made in Section 1. Directly on point for the present setting, Gupta et al. (2022) test the relationship between aggregate intellectual-capital efficiency and financial performance in Indian pharmaceutical firms and report a positive association, establishing the sectoral precedent this study extends into a dynamic, component-level framework; Al Momani et al. (2023) extend this line of inquiry to Jordanian pharmaceutical companies and likewise report a positive intellectual-capital performance nexus, suggesting the pattern generalises across knowledge-intensive pharmaceutical markets beyond India specifically.

2.3 Theoretical Framework

Four complementary perspectives are combined here. The resource-based view (Barney, 1991) holds that sustained competitive advantage arises from resources that are valuable, rare, inimitable and non-substitutable (VRIN), directing attention to intellectual-capital resources that competitors cannot easily replicate. The knowledge-based view (Grant, 1996) extends this by arguing that the decisive source of competitive value is the integration of distributed knowledge into productive capability- pharmaceutical R&D being a paradigm case, since a single molecule's commercial success depends on coordinating chemistry, toxicology, clinical, regulatory and manufacturing knowledge that resides in different parts of the organisation. Teece et al.'s (1997) dynamic-capabilities framework adds a temporal dimension, describing how firms adapt knowledge and organisational assets to shifts in technology and competitive conditions such as patent expiry, generic entry and regulatory reform; this temporal lens is directly relevant to the dynamic panel design adopted in Section 3, since it implies that a firm's capacity to convert intellectual capital into profit is itself expected to evolve rather than remain fixed across the sample period. Teece's (1986) complementary-assets theory explains how knowledge is commercialised- a process reflected in MVAIC through capital employed efficiency. Youndt et al. (2004) provide empirical grounding for combining these views, showing that returns depend on the configuration of human, structural and social capital investments rather than on any one investment alone- a configural logic that motivates examining both the aggregate MVAIC score and its individual components in this study. It is worth stating plainly that MVAIC captures accounting efficiency, not the rarity or inimitability that Barney (1991) requires of a strategic resource; the two should not be conflated when interpreting the results in Section 5.

2.4 Aggregate MVAIC and Profitability

Efficient use of human, organisational and productive resources is generally expected to raise ROA, and the evidence is reasonably consistent across settings: Gupta et al. (2022) report a positive MVAIC-performance association among Indian pharmaceutical firms, Ayinaddis et al. (2024) confirm a positive relationship in an emerging-market insurance setting, and Weqar et al. (2021) find the same pattern for BSE-listed Indian firms across several performance measures. Sector-diverse Indian evidence like a study on the sugar mill industry exhibited a positive intellectual-capital performance relationship (Sharma et al., 2024), suggesting the aggregate pattern documented for pharmaceuticals is not an artefact confined to one industry within the Indian listed universe. Dynamic-panel evidence corroborates the aggregate pattern outside pharmaceuticals as well: Vo and Tran (2021) report a positive intellectual-capital performance link for Vietnamese banks, Zheng et al. (2022) find that intellectual-capital efficiency is associated with both performance and risk-taking behaviour in an Asian banking panel, and, within India specifically, Barak and Sharma (2024) confirm a positive aggregate intellectual-capital performance association among Indian public-sector banks using GMM estimation, while Barak (2024) extends the comparison across public- and private-sector Indian banks and finds the aggregate association holds in both ownership types. This convergence of dynamic-panel evidence across banking and pharmaceutical settings in India strengthens the plausibility of a positive aggregate MVAIC-ROA relationship in the present sample, even though magnitude and significance continue to vary by industry, national context and MVAIC formulation- which is why the component-level analysis matters as much as the aggregate coefficient. Thus, hypothesis and research question are formulated as:

H1: MVAIC is positively associated with ROA.

RQ1: Do the four MVAIC components have heterogeneous relationships with ROA?

2.5 Human capital efficiency

Human capital efficiency captures value added per unit of employee expenditure, and positive associations with performance have been documented using dynamic-panel methods in China (Ting et al., 2020) and in India for a comparable Chinese manufacturing panel (Weqar et al., 2021; Xu & Li, 2022). Evidence from within India adds further texture: Chatterjee et al. (2021) find that the performance contribution of intellectual capital in Indian firms is moderated by firm age and gender composition, and Saha and Maji (2022) show that board-level Human capital diversity itself is associated with firm performance among top listed Indian firms, together suggesting that HCE's translation into profitability is contingent on organisational and governance characteristics rather than a fixed technical relationship. The dependency is not unconditional in a resource sense either: Youndt et al. (2004) show that the profitability contribution of human capital depends on complementary structural and relational capital, implying that employee-expenditure efficiency alone is an incomplete predictor of returns unless paired with the organisational systems that convert individual expertise into repeatable value. Thus, hypothesis is formulated as:

H2: HCE is positively associated with ROA.

2.6 Structural-Capital Efficiency

Previous research with the manufacturing sector of emerging markets panels indicates that structural capital had a positive impact on financial results, due to the fact that it enables individual expertise to be formalized and reproduced (Xu and Li (2022). In a long-term study of corporate governance and intellectual capital, Nawaz and Ohlrogge (2022) also conclude that knowledge held by individual employees is a less enduring performance factor than knowledge that is codified in the organisation. Public administrations in Mexico and Peru, they add, show that the effect of the structural capital on performance can be indirect, and not direct, because the former links the effect of human capital to the outcomes. This is directly related to understanding the mechanical HCE-SCE relationship (Pedraza Melo and De La Gala Velasquez, 2022). Within an Indian manufacturing context, Dharni and Jameel (2021) link patent-based intellectual-capital disclosures to firm performance, offering direct evidence that codified, IP-related organisational capital carries performance-relevant information in Indian industry specifically; Tjahjadi et al. (2024), studying Indonesian state-owned enterprises, further show that structural intellectual capital's performance contribution is channelled through open-innovation activity rather than operating in isolation. This is consistent with Grant's (1996) argument that sustainable advantage rests on knowledge integration rather than knowledge possession. Thus, hypothesis is formulated as:

H3: SCE is positively associated with ROA.

2.7 Relational-Capital Efficiency

Customer relationships, reputation, brand equity and commercial partnerships constitute relational resources that support market access, and commercialisation in pharmaceuticals depends heavily on distribution and marketing engagement with external stakeholders. The RCE measure used here, however, is an accounting proxy- marketing expenditure relative to value added- not a direct measure of customer loyalty, brand equity or reputational capital, and several interpretive caveats follow from that. High current expenditure could reflect market-defence activity or competitive pressure rather than value-creating relational investment, while a negative contemporaneous association could instead reflect firms raising commercial spending precisely when profitability is under pressure. Evidence on expenditure-based relational proxies is genuinely mixed elsewhere: Barak and Sharma (2023) report differential relational-capital effects across performance indicators in Indian banking, Yu et al. (2021) find that relational capital's link to financial performance in green supply-chain contexts depends on complementary governance mechanisms rather than holding unconditionally, and Pant et al. (2022), studying Indian supply chains directly, similarly find that relational capital's performance contribution is conditional on the structure of the buyer-supplier relationship rather than uniformly positive. Combined with the expenditure-return time lag already noted in Section 2.2 (Shivdas & Ray, 2021), there is no clear directional prior for RCE here; it may be positive, negative or insignificant, and is treated as an open research question rather than a hypothesis.

RQ2: What is the relationship between RCE and ROA?

2.8 Capital Employed Efficiency

Capital employed efficiency (CEE) is value added per unit of capital employed, capturing the productivity of the physical and financial asset base- manufacturing plant, quality-assurance equipment and distribution infrastructure being the relevant complementary assets in this sector (Teece, 1986). Positive CEE-performance associations have been reported across varied samples (Ayinaddis et al., 2024; Weqar et al., 2021; Bassetti et al., 2020), with Bassetti et al. (2020) offering a critical validation that identifies CEE as one of the more empirically reliable VAIC components. This suggests that effective deployment of productive capital can support profitability even in a predominantly knowledge-intensive industry. Thus, hypothesis is formulated as:

H4: CEE is positively associated with ROA.

2.9 Profitability Persistence and Leverage

Firm profitability tends to persist through incumbency advantages, switching costs, market-structure barriers and accumulated reputation. Nickell (1981) shows that fixed-effects estimators in dynamic panels with a lagged dependent variable are downward biased in short panels, motivating GMM estimation whenever lagged profitability enters as a regressor. Leverage, meanwhile, imposes financing costs and debt-servicing obligations that reduce net returns; the combination of high borrowing costs and long, uncertain R&D and commercialisation cycles can simultaneously burden interest payments and restrict resource-allocation flexibility. Negative leverage-ROA associations have been documented in Indian manufacturing (Panchal & Chand, 2023) and in Indian capital structure analysis more broadly (Shukla et al., 2024), and Ahmed et al. (2024) extend this evidence to manufacturing firms pursuing innovation-led strategies, finding that capital structure choices interact with innovation intensity in shaping performance- a combination directly relevant to R&D-intensive pharmaceutical firms. The negative pattern replicates specifically in pharmaceutical settings: Karim et al. (2023) find a negative leverage-performance association among Bangladeshi pharmaceutical firms, and Mathur et al. (2021) report a comparable pattern for Indian pharmaceutical companies once competitive intensity is accounted for. This cross-country consistency in a sector with similar financing and development-cycle characteristics to India's justifies leverage as a control variable and motivates a negative directional expectation. Thus, hypotheses are formulated as:

H5: Lagged ROA is positively associated with current ROA.

H6: Leverage is negatively associated with ROA.

2.10 Configurational Evidence Beyond the Sector

Evidence from outside pharmaceuticals reinforces the configurational reading of intellectual capital that motivates the present hypotheses. Essel (2025), studying listed manufacturing firms in Ghana, finds that intellectual capital's performance contribution operates partly through family-management structures rather than as a direct, unconditional effect, echoing the complementary-resource logic of Youndt et al. (2004). Similarly, Al Momani et al. (2023) and Tjahjadi et al. (2024) both report that intellectual-capital efficiency's link to performance in Jordanian pharmaceutical and Indonesian state-owned enterprise settings, respectively, depends on complementary organisational conditions rather than holding as a fixed technical ratio. Taken together with the India-specific evidence reviewed above, this body of work supports treating MVAIC's aggregate association with profitability as a step towards the component-level decomposition that forms the empirical core of this study.

3. METHODOLOGY

3.1 Data and Sample Construction

Firm-level data were obtained from the CMIE Prowess database of firms belonging to the Drugs & Pharmaceuticals sub-industry (Chemicals & chemical products). The first extraction consisted of a well-balanced panel of 372 firms observed each year from 2014-2024 (4,092 firm-year observations). Because the underlying accounting relationships were unrealistic, in that value added was assumed to be positive, human capital was strictly positive, and capital employed was strictly positive and observed, the underlying sample was reduced to 2,843 observations (335 firms) for which MVAIC and its components were computed. Only if all core-model variables (ROA, MVAIC, leverage, tangibility, size) were non-missing was the number of observations (firms) equal to 2692. In order to take advantage of the within-firm dynamics, the sample was then limited to firm-specific runs with at least four full years of observations, resulting in an unbalanced panel of 2,344 observations for 267 firms (summarised in Table 1). The last dynamic estimation sample consists of 2062 firm-year observations of 267 firms during 2014-2024. To limit the effects of extreme values, all continuous variables that were used as inputs to the estimating equations were winsorised at the 1st and 99th percentiles following the sample selection, in line with the pre-winsorisation audit performed which identified extreme skewness and kurtosis in several ratio variables.

Table 1. Sample Construction

Stage	Firm-year observations	Firms
Initial CMIE Prowess pharmaceutical panel, 2014-2024	4,092	372
Economically valid MVAIC observations	2,843	335
Complete core-model observations	2,692	333
Runs of at least four consecutive complete years	2,344	267
Final dynamic sample after lagging ROA	2,062	267

Source: Author's calculations from Stata. The final dynamic estimation period is 2014-2024. Variables were winsorised at the 1st and 99th percentiles after sample selection.

3.2 Variable Construction

Table 2. Variable Definitions

Variable	Definition	Construction
ROA	Return on assets	Profit after tax / total assets

VA	Value added	Operating profit + employee expenditure + depreciation and amortisation
HCE	Human capital efficiency	VA / employee expenditure
SCE	Structural capital efficiency	(VA − employee expenditure) / VA
RCE	Relational capital efficiency	Marketing expenditure / VA
CEE	Capital employed efficiency	VA / capital employed
MVAIC	Modified value added intellectual coefficient	HCE + SCE + RCE + CEE
Leverage	Debt intensity	Total debt / total assets
Tangibility	Fixed-asset intensity	Net fixed assets / total assets
Firm size	Firm scale	Natural logarithm of total assets

Value added, its three cost/resource components, and the four MVAIC efficiency ratios were constructed following the human-structural-relational classification of intellectual capital (Bontis, 1998), Pulic's (2000) original VAIC framework, and its extension to incorporate relational capital efficiency (Nazari & Herremans, 2007), as follows:
The economic-validity restrictions imposed on these ratios' denominators (Section 3.1) follow published critiques of VAIC's measurement assumptions (Ståhle et al., 2011) and validation evidence on the empirical reliability of VAIC's components, including capital employed efficiency (Bassetti et al., 2020).

3.3 Empirical Models

Aggregate MVAIC model:
$ROA_{it} = \alpha + \rho ROA_{i,t-1} + \beta_1 MVAIC_{it} + \ \beta_2 LEV_{it} + \beta_3 TANG_{it} + \beta_4 SIZE_{it} + \sum_t \gamma_t . Year_t \ + \ \mu_i + \epsilon_{it}$ (1)
Joint component model (supplementary- see Section 3.4 note on HCE/SCE collinearity):
$ROA_{it} = \alpha + \rho ROA_{i,t-1} + \beta_1 HCE_{it} + \beta_2 SCE_{it} + \beta_3 RCE_{it} + \beta_4 CEE_{it} + \ \beta_5 LEV_{it} + \beta_6 TANG_{it} + \beta_7 SIZE_{it} + \sum_t \gamma_t . Year_t \ + \ \mu_i + \epsilon_{it}$ (2)
Individual component models:
$ROA_{it} = \alpha + \rho ROA_{i,t-1} + \beta_1 IC_{it}^k + \ \beta_2 LEV_{it} + \beta_3 TANG_{it} + \beta_4 SIZE_{it} + \sum_t \gamma_t . Year_t \ + \ \mu_i + \epsilon_{it}$ (3)
where $IC_{it}^k \subset HCE_{it}, SCE_{it}, RCE_{it}$
$+ \mu_i$ is the firm-specific effect (estimated directly under fixed effects, differenced/instrumented out under GMM), γ_t are year-fixed effects, and ϵ_{it} is the idiosyncratic error.

3.4 Estimation Strategy

For each model there were three estimators. The estimated results from pooled OLS and fixed effects are considered as approximate lower and upper bounds on the true persistence coefficient since the lagged dependent variable is correlated with the unobserved firm-specific effect in the case of pooled OLS and the within-transformation of the dependent variable leads to correlation between the transformed lagged dependent variable and the transformed error (Nickell bias; Nickell, 1981) in the case of fixed effects. Two-step system GMM with Windmeijer-corrected standard errors and collapsed instruments (Arellano & Bond, 1991; Blundell & Bond, 1998; Windmeijer, 2005) is the preferred estimator with standard errors corrected for the clustering of observations within firms.Standard errors are clustered within firms and the preferred estimator is two-step system GMM with Windmeijer-corrected standard errors (Arellano & Bond, 1991; Blundell & Bond, 1998; Windmeijer, 2005). The MVAIC variable(s) of interest, ROA and leverage, were treated as predetermined/endogenous and instrumented with their own lag limits (2-3). The tangibility, size and year dummies were added as instruments in both the difference and level equations.
The Arellano-Bond test of first and second order serial correlation in differenced residuals (AR(1) should reject, while AR(2) should not) was used to test specification adequacy, as well as the Hansen and Sargan test of overidentifying restrictions (Hansen is reported as the primary test in view of its robustness to heteroskedasticity, while Sargan is a supplementary and non-robust cross-check test). Instruments were reduced to the level of the number of cross sectional units (267 firms) throughout using the instrument collapsing technique recommended by practitioners in implementing system GMM (Roodman, 2009). The mechanical relationship between human capital efficiency and structural capital efficiency (SCE = 1 − 1/HCE, as referenced in Section 2.6) as well as the high variance inflation factors in the joint-component model (when both components are entered together; Section 4.2) dictates that the joint-component model is reported as a robustness check and that the individual-component models (one MVAIC component entered at a time) are used as the baseline for interpreting each component's association to profitability. All estimations were conducted in Stata, with the built-in command regress used to estimate the pooled OLS models and the community-contributed command xtabond2 (Arellano-Bond/Blundell-Bond estimator, two-step robust SE) to estimate the fixed-effects models; the xtabond2 community-contributed command was used to estimate the system GMM models, which included the instrument-collapsing option to control for instrument proliferation.

4. RESULTS

4.1 Descriptive Statistics

Table 3 reports descriptive statistics for the winsorised variables in the final dynamic estimation sample (N = 2,062). Mean ROA is 6.3%, with a standard deviation of 7.2%, indicating that while the typical firm in the sample is modestly profitable, dispersion around that mean is wide relative to it- consistent with a sector where regulatory approval timing and product-portfolio maturity can generate substantial year-to-year variation across firms. Mean MVAIC is 3.872, driven predominantly by human capital efficiency (mean HCE = 2.815), with structural capital efficiency (mean SCE = 0.566), capital employed efficiency (mean CEE = 0.387) and relational capital efficiency (mean RCE = 0.101, SD = 0.122) contributing smaller and more compressed shares; the relatively low dispersion of RCE compared with HCE suggests that marketing-expenditure intensity is a more disciplined, narrowly-ranged choice across firms than employee-expenditure efficiency, which varies more with firm-specific scale and product mix. Mean leverage (0.227), tangibility (0.298) and firm size (mean ln(TA) = 8.036) are consistent with a moderately levered, moderately asset-tangible manufacturing sector, and the wide range in firm size (min 4.096 to max 12.468) confirms that the sample spans both small specialised manufacturers and large diversified pharmaceutical companies, supporting the inclusion of firm size as a control. The gap between the median (0.057) and mean (0.063) ROA is modest, indicating that the winsorisation applied at the 1st and 99th percentiles has curbed the influence of extreme outliers without materially distorting the central tendency of the profitability measure that the dynamic models below seek to explain.

Table 3. Descriptive Statistics (winsorised, dynamic estimation sample, N = 2,062)

Variable	Mean	SD	Min	p25	Median	p75	Max
ROA	0.063	0.072	-0.153	0.020	0.057	0.102	0.277
MVAIC	3.872	1.445	0.374	2.945	3.652	4.573	8.873
HCE	2.815	1.284	0.700	1.940	2.565	3.408	7.525
SCE	0.566	0.214	-0.429	0.485	0.610	0.707	0.867
RCE	0.101	0.122	0.001	0.026	0.059	0.130	0.735
CEE	0.387	0.210	0.052	0.246	0.354	0.486	1.165
Leverage	0.227	0.190	0.001	0.076	0.198	0.331	0.971
Tangibility	0.298	0.149	0.038	0.182	0.298	0.393	0.711
Firm size (ln TA)	8.036	1.872	4.096	6.790	7.791	9.274	12.468

*Source: Author's calculations from Stata. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.*

4.2 Correlation Matrix and Multicollinearity

Table 4, Panel A reports pairwise correlations among the core-model variables. ROA is positively correlated with MVAIC (r = 0.504) and firm size (r = 0.166), and negatively correlated with leverage (r = -0.493) and tangibility (r = -0.148); all core-model pairs are significant at the 1% level except MVAIC-tangibility, significant at the 5% level. The moderate-to-strong MVAIC-ROA correlation is a useful sanity check ahead of the multivariate results in Section 4.3, though it cannot itself distinguish an intellectual capital effect from reverse causality running from profitability to intellectual capital spending- the concern the system GMM specification is designed to address. The leverage-ROA correlation (r = -0.493) is notably the strongest bivariate relationship in Panel A, foreshadowing the consistently significant negative leverage coefficient reported across all model specifications in Sections 4.3 and 4.4. Panel B reports correlations among the four MVAIC components. HCE and SCE are highly correlated (r = 0.812), consistent with their shared mechanical construction (SCE = 1 – 1/HCE); RCE is negatively correlated with both HCE and SCE, foreshadowing the component-level divergence reported in Section 4.4, and CEE is only weakly correlated with the other three components, indicating that productive capital efficiency varies largely independently of the sample's human- and structural capital efficiency. Variance inflation factors from the auxiliary pooled regression underlying the aggregate model are modest (mean VIF = 1.77; maximum = 2.12), indicating no material multicollinearity concern for the aggregate MVAIC specification. In the joint-component auxiliary regression, VIFs for SCE (3.14) and HCE (2.96) are elevated relative to the other regressors (all below 1.7), which is the basis for treating the joint-component model in Table 6 as supplementary rather than as evidence of four independent marginal effects.

Table 4. Correlation Matrix (N = 2,062)

Panel A: Core model variables

	ROA	MVAIC	Leverage	Tangibility	Firm size
ROA	1.000				
MVAIC	0.504***	1.000			
Leverage	-0.493***	-0.100***	1.000		
Tangibility	-0.148***	0.049**	0.274***	1.000	

Firm size	0.166***	0.161***	-0.106***	-0.155***	1.000

Panel B: MVAIC components

	HCE	SCE	RCE	CEE	MVAIC
HCE	1.000				
SCE	0.812***	1.000			
RCE	-0.221***	-0.257***	1.000		
CEE	-0.053**	-0.048**	0.036*	1.000	
MVAIC	0.980***	0.842***	-0.140***	0.102***	1.000

*Source: Author's calculations from Stata. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.*

4.3 Aggregate MVAIC Models (H5, H1, H6)

Table 5 reports the aggregate MVAIC models. Lagged ROA is positive and significant at the 1% level across all three estimators, supporting H5 (profitability persistence): the pooled OLS estimate (0.509) and fixed-effects estimate (0.123) bracket the system GMM estimate (0.354), consistent with the expected direction of Nickell and heterogeneity bias and providing an internal plausibility check on the GMM result. MVAIC is positive and significant in all three models- pooled OLS (0.015), fixed effects (0.030), system GMM (0.012)- supporting H1. Leverage is negative and significant at the 1% level in all three models, supporting H6. Tangibility is negative and significant only in fixed effects; firm size is not significant in the preferred system GMM specification. Diagnostics for the system GMM model are satisfactory: AR(2) is not rejected at the 5% level ($p = 0.053$, borderline), and neither Hansen ($p = 0.343$) nor Sargan ($p = 0.102$) rejects the instrument set, with the difference-in-Hansen test for the level-equation instruments also non-rejecting ($p = 0.858$).

Table 5. Dynamic Profitability Models (Aggregate MVAIC)

	Pooled OLS	Fixed effects	System GMM
Lagged ROA	0.509*** (0.035)	0.123*** (0.034)	0.354*** (0.065)
MVAIC	0.015*** (0.002)	0.030*** (0.002)	0.012** (0.005)
Leverage	-0.080*** (0.010)	-0.133*** (0.014)	-0.096*** (0.036)
Tangibility	-0.016 (0.010)	-0.084*** (0.018)	-0.023 (0.017)
Firm size	-0.000 (0.001)	-0.010* (0.005)	0.001 (0.001)
Firm effects	No	Yes	Yes
Year effects	Yes	Yes	Yes
Observations	2,062	2,062	2,062
Firms	267	267	267
Instruments	–	–	21
F-test, p-value	0.000	0.000	0.000
AR(1), p-value	–	–	0.000
AR(2), p-value	–	–	0.053
Sargan test, p-value	–	–	0.102
Hansen test, p-value	–	–	0.343
Diff-in-Hansen (level instr.), p-value	–	–	0.858

*Source: Author's calculations from Stata. Cluster-robust standard errors in parentheses for pooled OLS and fixed effects; two-step, robust standard errors in parentheses for system GMM. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.*

4.4 Component-Level Models (H2-H4, RQ1, RQ2)

Table 6 reports system GMM estimates decomposing MVAIC into its four components, both jointly and individually. In the individual-component models, structural capital efficiency (SCE = 0.095, $p < 0.01$) and capital employed efficiency (CEE = 0.075, $p < 0.10$) are positively associated with ROA, partially supporting H3 and H4; human capital efficiency is positive but only marginally significant (HCE = 0.011, $p < 0.10$), offering weak support for H2. Relational capital efficiency is negative and significant in both the individual (RCE = -0.143, $p < 0.05$) and joint (RCE = -0.102, $p < 0.05$) specifications, answering RQ2 in the negative direction. When all four components are entered jointly, RCE remains negative and CEE remains positive and significant, while HCE and SCE lose individual significance-consistent with their documented collinearity (Section 4.2) and answering RQ1: the components of MVAIC exhibit heterogeneous, and in the case of RCE, opposing associations with profitability, so the aggregate MVAIC result in Table 5 should not be read as evidence that all four components contribute uniformly. This divergence between a positive aggregate coefficient and a negative individual RCE coefficient is itself informative: it shows that the aggregate MVAIC score can mask a component actively working against the direction the headline result implies, which is precisely the configurational pattern Youndt et al. (2004) predict and which motivates reporting individual-component models as the primary basis for interpretation rather than the aggregate score alone. The persistence coefficients in Table 6 are also informative in their own right: they decline from around 0.34-0.40 in the single-component models to 0.282 in the all-components specification, consistent with the four components jointly absorbing some of the within-firm variation that the single-component models leave for the lagged dependent variable to capture, and providing a further internal check that the components are not simply re-labelling the same persistence already identified in Table 5. Diagnostics are satisfactory across all five specifications: AR(2) is not rejected at the 5% level in any model, Hansen is not rejected in any model ($p \geq 0.270$), and the difference-in-Hansen test for level instruments does not reject in any model. The one diagnostic flag is the Sargan test in the CEE-only model ($p = 0.007$), which is not robust to heteroskedasticity and is superseded here by the non-rejecting Hansen test ($p = 0.357$) for that same specification; this is noted as a limitation of the CEE-only result in the Discussion.

Table 6. System GMM Models (MVAIC Components)

	All components	HCE only	SCE only	RCE only	CEE only
Lagged ROA	0.282*** (0.062)	0.373*** (0.068)	0.361*** (0.064)	0.399*** (0.067)	0.343*** (0.060)
HCE	0.004 (0.008)	0.011* (0.006)	–	–	–
SCE	0.056 (0.040)	–	0.095*** (0.031)	–	–
RCE	-0.102** (0.048)	–	–	-0.143** (0.058)	–
CEE	0.064** (0.031)	–	–	–	0.075* (0.041)
Leverage	-0.074* (0.043)	-0.102*** (0.037)	-0.088** (0.040)	-0.122*** (0.046)	-0.093** (0.046)
Tangibility	-0.053** (0.021)	-0.020 (0.017)	-0.030 (0.018)	-0.032 (0.023)	-0.024 (0.021)
Firm size	0.002 (0.001)	0.001 (0.001)	-0.000 (0.001)	0.001 (0.001)	0.004*** (0.001)
Firm/Year effects	Yes / Yes	Yes / Yes	Yes / Yes	Yes / Yes	Yes / Yes
Observations	2,062	2,062	2,062	2,062	2,062
Firms	267	267	267	267	267
Instruments	30	21	21	21	21
AR(2), p-value	0.186	0.057	0.077	0.115	0.074
Sargan test, p-value	0.115	0.129	0.058	0.268	0.007
Hansen test, p-value	0.774	0.389	0.270	0.685	0.357
Diff-in-Hansen, p-value	0.502	0.800	0.746	0.756	0.260

*Source: Author's calculations from Stata. Two-step, robust standard errors in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. "All components" is a supplementary specification (see Section 3.4 note on HCE/SCE collinearity); the single-component models are the preferred specification for interpreting each component individually.*

5. DISCUSSION

5.1 Profitability Persistence

The positive association between lagged ROA and current ROA confirms that pharmaceutical firm profitability in India is persistent (pooled OLS $\beta = 0.509$; fixed effects $\beta = 0.123$; system GMM $\beta = 0.354$, all $p < 0.01$), and the system-GMM persistence estimate lying between the upward-biased pooled OLS and downward-biased dynamic fixed-effects estimates is consistent with the estimator hierarchy anticipated by Nickell (1981). A bracketing pattern gives confidence to the specification. Structurally, high profitability is sustainable where firms hold market advantages that are not easily lost within a single year- a portfolio of proprietary products, accumulated regulatory experience, or an established distribution network. This persistence estimate is also broadly consistent with Mahor and Banerji's (2023) cointegration-based evidence that Indian pharmaceutical profitability exhibits both short- and long-run dependency on firm-level fundamentals, reinforcing that a single-period, static view of profitability would misrepresent how this industry's competitive positions actually evolve.

5.2 Aggregate MVAIC and Profitability

The positive and statistically significant overall association between MVAIC and ROA ($\beta = 0.015$, 0.030 and 0.012 in pooled OLS, fixed effects and system GMM respectively) is the key confirming result of the study. This finding is in line with the hypothesis that the overall efficiency of knowledge-based, organisational and productive capital resources is linked to better financial performance. The results are consistent with Weqar et al. (2021), who found positive aggregate VAIC–ROA relationships for BSE-listed firms in India, with Ayinaddis et al. (2024), who found a positive MVAIC-performance relationship in an emerging-market insurance context, and with dynamic-panel evidence from banking settings (Vo & Tran, 2021; Zheng et al., 2022; Barak, 2024; Barak & Sharma, 2024), which shows the aggregate pattern is not an artefact of static estimation and holds across both public- and private-sector ownership structures within India specifically. In the Indian pharmaceutical industry, the most directly parallel evidence is Gupta et al. (2022), and the pattern extends regionally to Al Momani et al.'s (2023) evidence from Jordanian pharmaceutical firms. The aggregate result should not, however, be read as if all components contribute positively and uniformly; heterogeneity at the component level, discussed next, is not captured by the overall coefficient.

5.3 Human and Structural Capital

The individual-component results are more intricate than the aggregate result suggests. Employee-expenditure efficiency is positively but only marginally associated with ROA ($\beta = 0.011$, $p < 0.10$), consistent with Ting et al. (2020), who find HCE effects to be positive but context-dependent, and with the theoretical expectation that HCE's contribution to profitability depends on complementary structural conditions. This marginal result also aligns with Chatterjee et al.'s (2021) finding that intellectual capital's performance contribution in Indian firms is moderated by organisational characteristics such as firm age, and with Saha and Maji's (2022) evidence that board-level Human capital composition, not merely employee-expenditure intensity, carries independent performance relevance- both consistent with a weak, conditional rather than strong, unconditional HCE effect. Codified organisational knowledge shows a more robust positive association with profitability ($\beta = 0.095$, $p < 0.01$). Theoretical support comes from Grant's (1996) knowledge-integration perspective- that competitive advantage rests on embedded, repeatable processes rather than any one individual's expertise- and is echoed empirically by Xu and Li (2022) in an emerging-market manufacturing context, by Nawaz and Ohlrogge (2022), whose long-run governance evidence similarly finds codified capital a more durable performance driver than individually held knowledge, and by Dharni and Jameel (2021), whose Indian manufacturing evidence links patent-based structural capital directly to firm performance. The stronger and more stable SCE result relative to HCE plausibly reflects the relative stability of codified organisational capital across production and operational cycles. Given the mechanical relationship between HCE and SCE established in Section 3.4, the individual-component models, not the joint coefficients in Table 6 (column 1), should be treated as the basis for interpreting each measure.

5.4 Negative Relational capital efficiency

The study's central nuance is the negative and significant RCE coefficient. This does not suggest that customer relationships, reputation or market access destroy value; the coefficient captures the association between an expenditure-based RCE proxy and contemporaneous accounting profitability, and several mechanisms could produce this pattern. Financial returns from marketing expenditure are realised in the same period the expenditure is recorded, while commercial and reputational returns typically materialise later, so the benefit of the spend is not yet reflected in current-period profitability. High marketing spend could equally signal competitive pressure or market-defence activity- plausible in a sector facing generic competition- rather than discretionary, value-creating investment. A reverse-adjustment mechanism is also possible: firms with weaker recent profitability may raise commercial spending precisely when current profitability drops. This ambiguity is not unique to the present setting- Barak and Sharma (2023) report differential relational capital effects in Indian banking, Yu et al. (2021) similarly find that relational capital's link to financial performance is conditional rather than automatic, and Pant et al. (2022), studying Indian supply chains, report that relational capital's performance contribution depends on the structure of the underlying buyer-supplier relationship rather than holding as a direct effect- a pattern consistent with the present finding that a purely expenditure-based relational proxy need not translate into contemporaneous profitability. The individual-component RCE coefficient of −0.143 ($p < 0.05$), combined with the sample RCE standard deviation of 0.122 (Table 3), implies that a one-standard-deviation increase in RCE is associated with a decline in ROA of roughly 1.7 percentage points relative to a sample mean ROA of 6.3%- a non-trivial short-run association that could plausibly be moderated by delayed effects not directly tested here.

5.5 Capital Employed Efficiency

The positive association between efficient deployment of physical and financial capital and ROA is consistent with the complementary-assets view (Teece, 1986): knowledge resources require productive and organisational support- here, pharmaceutical manufacturing and distribution capacity- to be converted into financial value. Bassetti et al. (2020) confirm CEE as one of the more empirically supported VAIC components, Weqar et al. (2021) report positive CEE-performance associations, and Tömöri et al. (2022) show that efficient capital deployment helps offset the financial-flexibility constraints that R&D-heavy pharmaceutical spending otherwise creates. The comparatively larger CEE coefficient among the individual-component system GMM models than in the fixed-effects specification of the aggregate model is also consistent with the view that productive capital efficiency responds relatively quickly to investment decisions, in contrast to the slower-accumulating human- and structural capital channels, which is plausible given that capital employed efficiency reflects plant utilisation and asset turnover rather than knowledge that must first be built up over multiple periods. The individual CEE evidence here is nonetheless weaker than the aggregate MVAIC and SCE results. The CEE-only model's Sargan test rejects ($p = 0.007$) while the robust Hansen test does not ($p = 0.357$); since the two diagnostics are not equivalent, both are reported rather than one being favoured over the other by omission.

5.6 Leverage and Financial Flexibility

The negative relationship between leverage and ROA holds consistently across all three estimators (β = -0.080, -0.133 and -0.096 for pooled OLS, fixed effects and system GMM respectively, all $p < 0.01$). Debt costs are a persistent drain on resources that might otherwise finance long-horizon R&D, clinical-trial and regulatory-approval activity, and higher leverage can further raise financial-distress risk and compress managerial appetite for the long-horizon contracts typical of pharmaceutical innovation. The pattern is corroborated by Panchal and Chand (2023) for Indian manufacturing, by Shukla et al. (2024) for Indian capital structure more broadly, by Ahmed et al. (2024), who find that capital structure choices interact with innovation strategy in shaping manufacturing performance, and- directly in-sector- by Karim et al. (2023) for Bangladeshi pharmaceutical firms and Mathur et al. (2021) for Indian pharmaceutical firms specifically, indicating that the negative leverage-profitability association in R&D-intensive pharmaceutical firms is not specific to this sample or period.

5.7 Synthesis and Bounded Interpretation

The findings suggest that overall MVAIC efficiency is consistently and positively correlated with the profitability of pharmaceutical companies in India, while concealing heterogeneous relationships at the component level. Organisational capital efficiency (SCE) and productive capital efficiency (CEE) are the more consistently positive contributors; the negative relationship for RCE means expenditure-based relational proxies should be interpreted with caution, with the temporal dimension of commercial expenditure treated as central rather than incidental to that interpretation. Read together, the pattern is consistent with a resource-conversion story rather than a resource-accumulation story: it is not simply how much a firm spends across the four MVAIC categories that predicts profitability, but how effectively that spending is embedded in codified systems (SCE) and productive capacity (CEE), with human capital (HCE) contributing weakly on its own and relational spend (RCE) showing no contemporaneous payoff at all. The system-GMM approach mitigates- but does not eliminate- endogeneity concerns arising from the simultaneous determination of intellectual capital investment and profitability; all reported relationships are associations under the maintained system-GMM identifying assumptions, not causal effects. The borderline AR(2) result for the aggregate model ($p = 0.053$) and the diagnostic disagreement in the CEE-only model (Sargan $p = 0.007$, Hansen $p = 0.357$) are limitations to inferential precision that are reported transparently alongside the substantive findings rather than set aside.

5.8 Robustness Considerations

Two features of the results reported above merit explicit robustness comment rather than being absorbed silently into the summary in Section 5.7. First, the mechanical HCE-SCE relationship documented in Section 3.4 means the joint-component model in Table 6 cannot be read as four independent marginal effects; the individual-component models, which avoid this collinearity by construction, are therefore the specification on which H2-H4 and RQ2 are evaluated, consistent with the treatment recommended by Bassetti et al. (2020) for VAIC-based component analysis generally. Second, the persistence of the core findings across pooled OLS, fixed effects and system GMM- same signs, broadly consistent magnitudes, and a system-GMM persistence coefficient that falls inside the range implied by the two conventional bounds- provides an internal consistency check of the kind advocated by Roodman (2009) for applied system-GMM work, even though it does not substitute for the formal Hansen, Sargan and Arellano-Bond diagnostics reported alongside each model. Neither consideration overturns the substantive findings, but both qualify how confidently the component-level coefficients, in particular, should be treated as precise point estimates rather than directionally informative associations.

6. Implications and Limitations

6.1 Theoretical Implications

The results lend support to a configurational model of intellectual capital, which posits that a positive overall association between the MVAIC is possible while the component relationships between the parts are materially different, suggesting that knowledge resources add value not as a uniform, additive contribution but through combinations. The outside-the-present sector evidence presented by Essel (2025) for the performance contribution of intellectual capital in family-managed manufacturing firms in Ghana and Tjahjadi et al. (2024) for open innovation in the Indonesian government-owned enterprises suggests that the pattern of heterogeneity presented here is not a peculiar feature of the Indian pharmaceutical sector. The higher score for structural capital is in line with the knowledge-based view's focus on knowledge integration (Grant, 1996) and with the complementary asset argument, which suggests that specialised knowledge will only be commercially appropriated with the help of organisational and productive assets (Teece, 1986). Simultaneously, the negative relationship of the relational capital relationship proves that spending-based accounting proxies must not be confused with resource-based views as they are based on the conversion efficiency and not the scarcity or inimitability of the resources being converted.

6.2 Managerial Implications

Indian pharmaceutical companies pursuing the profitability from investments in intellectual capital should focus more on the codification and institutionalisation of the organisation's knowledge- systems, processes and repeatable routines- than on the undifferentiated rise in the total amount of investment in intellectual capital, as the efficiency of structural capital demonstrates a stronger individual link with ROA. This finding is consistent with that of Saha and Maji (2022) who found that the Human capital result does not have a clear link to performance, but rather the Human capital composition does, which implies that firms can benefit more from the organization and governance of human capital than from the intensity of their costs. Marketing and commercial spending should not be regarded as a consistent positive investment, but rather as a measure of realised value creation; the negative RCE association suggests that marketing intensity as a share of value added in the shorter term does not necessarily lead to profitability, and companies might prefer to measure relational expenditure in terms of longer-term commercial results, not just accounting returns. Firms with highly leveraged balance sheets must balance the possibility of the imposed restriction on flexibility in the allocation of resources against the long and uncertain time horizon of pharmaceutical R&D and regulatory investments. Finally, the sustainability of the profits described in Section 5.1 means that competitive positions based on regulatory, scientific and distribution resources built up over time are not permanent, but can only be maintained through continuous investment in these resources and not through periodical interventions.

6.3 Policy and Reporting Implications

Regarding the impact of structural and capital employed efficiency on profitability, the positive relationship might imply that enhancing efficiency in these skills could have a positive impact on profitability for the domestic pharmaceutical sector, as well as on innovation. This negative leverage-profitability relationship for R&D-intensive pharmaceutical companies may be partly mitigated by the financing conditions that make debt financing more affordable or flexible for these companies, as suggested by Ahmed et al. (2024) for the general capital structure relationship of innovation-focused manufacturing companies. The lack of clarity in what is meant by relating to the relational capital finding also suggests that there is a need for a disclosure gap – more granular reporting of marketing and commercial expenditure, separately from other selling costs, would enable a more precise assessment of relational capital efficiency in future research and regulatory review and would help identify expenditure focused on market expansion from expenditure based on a defensive strategy.

6.4 Limitations and Future Research

This study has a few limitations. The accounting efficiency to turn tangible resources into MVAIC is used as a proxy but does not give any indication of the scarcity, inimitability or strategic value of the resource/capital used in the conversion and cannot be regarded as a measure of sustainable competitive advantage in the sense of the resource-based-view (Ståhle et al., 2011). The four years of annual data requirement for a true within-firm dynamic panel can over-represent the firms reporting in an irregular manner and therefore may not be representative of the entire Indian pharmaceutical industry. The RCE measure itself is designed from one single accounting line – marketing expenditure – and is not able to distinguish marketing expenditures aimed at market share defence from those focusing on market or product penetration, which plausibly has different profitability implications, but cannot be separated with the current data the model is based on. The dynamic specification relaxes several endogeneity concerns, but not as conclusively as one might like: the AR(2) test is nearly significant ($p = 0.053$) in the aggregate model; and the CEE-only model has a diagnostic disagreement between the Sargan ($p = 0.007$) and Hansen ($p = 0.357$) tests, with both tests reported but neither decisively beaten. All reported relationships are associations (as opposed to causal effects), under the maintained system-GMM, identifying assumptions. Future research may explicitly take into account lagged or distributed-lag specifications of RCE, as the short-run negative relationship reported here might be different in the long run; incorporate other performance measures, such as return on equity or market-based measures; assess component-level heterogeneity at a more granular level of expenditure disclosure than is currently available; and explore the relationship across nations, testing whether the short-run negative relationship between RCE is specific to the Indian pharmaceutical industry or generalises to other knowledge-intensive emerging-market sectors.

7. CONCLUSION

The aim of this study was to see if the efficiency of the use of intellectual capital (MVAIC and its components) is related to the profitability of the Indian listed drug and pharmaceutical companies using the two-step system GMM as the preferred estimator. The results of the analysis are consistent with the hypothesis that intellectual capital efficiency is a determinant of firm profitability net of leverage, tangibility, size and unobserved firm and year effects as the lagged ROA is positive and significant for the entire period, and the aggregate MVAIC is positively and significantly related to the ROA for all three types of estimators. The main contribution of the study is the component-level analysis, which demonstrates that this overall efficiency figure does not apply to all three efficiency measures—human, structural, or relational, and capital employed. The human capital efficiency is only a weak positive component and the relational capital efficiency is a weak negative component, when only considered on their own, while structural and capital employed efficiency are positive and stronger. This has been attributed to the mismatch in the recognition of marketing expenditure and the commercial return from the relationship with the customer and market, not to any intrinsic harm. The study's value, therefore, is not just to show that intellectual capital is important, but that there are varying component relationships across aggregate efficiencies and at varying time periods. The results support the argument for a dynamic, component-based analysis and call into question the limitations of MVAIC. In a field where knowledge, regulation and commercialisation are so intertwined and as in pharmaceuticals, a measure of so simple a number as “efficiency of intellectual capital” in treating it as a single entity would have masked just the kind of distinction this study's component construction was meant to expose.

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