International Research Journal of Multidisciplinary Scope (IRJMS), 2025; 6(1):911-926

Original Article | ISSN (O): 2582-631X DOI: 10.47857/irjms.2025.v06i01.02928

The Intellectual Capital-Performance Nexus: Analyzing Financial Returns through Static and Dynamic Models

Anchal Bansal*, Silender Singh, Priya Bansal

Department of Commerce, Chaudhary Devi Lal University Haryana, India. *Corresponding Author's Email: k20621092@gmail.com

Abstract

The present research inspects the correlation amid intellectual capital (IC) and the financial performance (FP) of firms listed in the NSE 500 index. The evaluation is grounded on data obtained from the CMIE PROWESS database, encompassing the decades 2014 to 2023. The sample for this study comprises 237 companies representing seven distinct industries. The present work utilizes the MVAIC model, which enhances the conventional VAIC approach by rectifying significant deficiencies identified in previous Indian studies, so resulting in increased accuracy and robustness. The results indicate a strong and favourable correlation between the efficiency of (IC) and critical FP parameters including Return on Equity (ROE), Return on Assets (ROA), and Return on Capital Employed (ROCE). This holds particularly true for SCVA and VACE, since they demonstrate a substantial and favourable impact on these measures, whereas, for VAHU, there is no statistically significant effect. The recently implemented variable VARCE exhibits a robust association with both ROE and ROA. The implementation of a dynamic panel model utilizing the generalized method of moments (GMM) underscores the importance of lagged variables. Incorporating the lagged dependent variable into the GMM dynamic panel model reveals its substantial influence on the current FP metrics. The substantial impact of the dependent variable highlights the enduring nature of FP, indicating that companies with robust historical performance are more inclined to sustain or enhance their financial results.

Keywords: Dynamic Panel Estimation, FP, GMM Model, Intellectual Capital, MVAIC, Panel Data.

Introduction

The worldwide transition to a knowledge-based economy has fundamentally altered how enterprises generate and maintain value. Within this emerging economic framework, the focus has shifted from conventional physical assets like machines and buildings to intangible assets that are less physical but equally, if not more, important. Of all the intangible assets, intellectual capital (IC) is particularly important in driving competitive advantage, innovation, and long-term operational success (1, 2). IC signifies expertise, relationships, and processes that enable organizations to create value and achieve strategic objectives. It is generally categorized into three distinct components: Human capital (HC), structural capital (SC), and Relational capital (RC) (3). HC includes the expertise and creativity of the workforce, which are essential for innovation and problem-solving within organizations (4). SC encompasses the processes, patents, databases, and other infrastructure that allow a firm to function effectively and efficiently (5). Ultimately, RC refers to the relationships a corporation maintains with its external stakeholders, including clients, suppliers, and collaborators. The company's market presence and growth are contingent upon these relationships (6). In the contemporary business landscape, the strategic management of IC has become increasingly important. Companies that can use and proficiently manage their intellectual capital are more strategically positioned to innovate, adapt to changes, and sustain competitive advantages in swiftly moving markets (7). The significance of IC is particularly evident in industries that are heavily reliant on knowledge and innovation, such as technology, pharmaceuticals, and finance, where the ability to generate, protect, and leverage knowledge can determine success or failure (8). The effect of IC on FP is profound, despite its intangible nature. Enhancing customer satisfaction, driving financial performance (FP), and improving operational efficiency are all potential benefits of companies with robust internal controls (9). For instance, companies that spend in HC through training and

(Received 23rd October 2024; Accepted 28th January 2025; Published 31st January 2025)

development are likely to see improvements in productivity and innovation (3,5). Similarly, companies that build robust SC—through efficient processes and innovation infrastructure—can better withstand market pressures and sustain long-term growth (5). RC also plays a pivotal role, as strong relationships with stakeholders can lead to customer loyalty, better supply chain management, and more favorable financing terms (10). Financial accounts may understate the true worth of intangible assets like IC because traditional accounting methods fail to adequately record their value (11). Researchers and practitioners have responded to this challenge by creating more sophisticated models and metrics for evaluating (IC). The Value-Added Intellectual Coefficient (VAIC) model evaluates the efficacy of IC in generating value within an organization. The methodological approach is a significant impediment that must be overcome during the examination of the influence of IC on an FP. In the past, a substantial amount of research has been dependent on static models, such as ordinary least squares (OLS) and fixed-effects models. These models presuppose that the correlation between IC and company success is both linear and constant over time. Nevertheless, it is plausible that this assumption may not comprehensively capture the intricacy and ever-changing nature of IC, which evolves in reaction to both internal and external factors. To more effectively handle the inherent issues of endogeneity and autocorrelation in static models, a recent study has suggested the use of dynamic panel data estimate approaches. These techniques include the GMM technique to solve the challenge mentioned above. By integrating instrumental variables and lagged dependent variables, researchers can improve the objectivity and accuracy of evaluating the relationship between IC and FP (12). Additionally, dynamic models consider the bidirectional nature of this link, implying that the company's past success could potentially impact the future efficiency of the IC. Static models neglect to account for the feedback loop that results from this phenomenon (13). The current study aims to expand the examination of intellectual capital (IC) in India by the application of Modified VAIC, or MVAIC. MVAIC assesses IC effectiveness more thoroughly (14–16). The research addresses several research gaps and enhances the existing literature by utilising the currently available dataset. Initially, the IC is assessed for its effectiveness using the Modified Value-added method. This method overcomes the constraints of prior Indian research and provides a higher degree of precision and dependability in comparison to the conventional VAIC model in which the most important element of IC i.e. relational capital is not included. Furthermore, the use of more advanced econometric models, such as the Generalized Method of Moments (GMM), to account for endogeneity and dynamic relationships between IC and FP remains underexplored. This omission prevents a nuanced understanding of the causal effects and long-term impacts of intellectual capital. By incorporating the GMM model, this research ensures a more robust analysis of dynamic relationships between IC and FP, addressing potential endogeneity issues. Furthermore, this study extends the application of the MVAIC model to firms from seven different industries, thereby contributing to a broader understanding of how intellectual capital impacts performance in diverse industrial settings.

Methodology

Theoretical Perspectives on IC and Performance Dynamics

The relationship between IC and FP can be explained through several theoretical mechanisms rooted in the resource-based view (RBV) and dynamic capabilities theory. Human capital (HC), which includes the knowledge, skills, and creativity of employees, directly drives firm performance by fostering innovation, enhancing productivity, and improving strategic decision-making, all of which contribute to higher profitability and competitive advantage. Structural capital (SC), consisting of organizational processes, intellectual property, and technological assets, provides the necessary infrastructure for leveraging HC effectively. By improving operational efficiency, facilitating knowledge transfer, and reducing costs, SC enhances financial outcomes such as profitability and return on assets (ROA). Relational capital (RC), which encompasses relationships with external stakeholders such as customers, suppliers, and partners, further boosts performance by enhancing customer loyalty, enabling strategic partnerships, and improving market access, which drives revenue growth. The synergistic interaction between HC, SC, and RC creates compounded effects that amplify their individual contributions to financial performance. When these components work together, firms are better positioned to innovate, optimize operations, and strengthen market relationships, ultimately leading to enhanced financial results like return on equity (ROE) and market value. Thus, IC acts as a vital resource that drives firm performance, emphasizing the importance of its effective management in achieving sustainable competitive advantage.

Overview of IC

IC is acknowledged as a vital determinant of organizational value in knowledge-based economies. In the latter part of the 20th century, The notion of IC became significant as organizations recognized the value of intangible assets in maintaining an edge over competitors. The initial pioneers divided IC into three primary categories: HC, SC, and RC, which constituted the foundational framework. HC denotes the intellect, skills, and proficiency that employees possess. SC encompasses the intellectual property, databases, and organizational processes that facilitate HC. RC constitutes the foundation of the relationships formed with external stakeholders, including purchasers, merchants, and collaborators. This classification has developed into a well-recognized paradigm in the domain of IC research and application. Conflicting conclusions have been published in the previous research concerning the influence of IC on FP, despite substantial study efforts. For example, it was discovered that the performance of firms, particularly those in knowledge-intensive industries, was substantially influenced by all three components of IC (17). In the same vein, it was found that the invention and market value of the firm were substantially improved by IC, specifically HC, and SC (18). Certain researchers have examined the capacity of various components of IC to generate value and their contribution to firm expansion (19, 20). The nexus between IC and the FP of enterprises has been contested in many studies (21, 22). However, the data showed contradictory empirical findings. Nevertheless, most research has demonstrated that a company's IC significantly influences its performance (9, 23–26). Nevertheless, several research has documented exceptions, suggesting either a lack of relationship or a notable inverse link between profitability and the intellectual capital coefficient (27, 28). The complex connection between IC and organisational success is underscored by the varied results in the literature. While the overarching trend suggests that IC is a significant asset, its effects might vary considerably based on the methods of management and utilization within different organizational and industry settings.

Null Hypothesis 1: No statistically significant relationship exists between IC and FP.

Human Capital

The significance of HC as the primary component of IC is well recognized due to its direct impact on innovation and strategic rejuvenation within businesses. Comprehensive research has verified a definitive association between HC and organizational performance, underscoring its significance in enhancing productivity, innovation, and competitiveness. Organizations possessing elevated levels of HC were generally surpassed in FP and innovation by their counterparts (29). Likewise, a meta-analysis was performed in a study that confirmed the advantageous impact of HC on corporate success across several sectors (30). HC influences performance, although not all studies have demonstrated statistical significance. HC influenced innovation, its direct influence on company success was ambiguous (31). This implies that the value of HC may be attained indirectly via alternative mechanisms, such as enhanced innovative potential or refined organisational processes.

Null Hypothesis 2: HC has no significant effect on the performance of the firm.

Structural Capital

The additional crucial element of intelligence capital (IC) is SC, which encompasses the organisational processes, methods, and intellectual property that facilitate the efficient utilisation of HC. Several empirical investigations have shown that a strong SC is important for increasing both productivity and creativity. Additionally, it is pointed out in a study that all non-humanoid information sources within the organization are incorporated by SC (32). The company's value is augmented beyond its tangible assets through the utilisation of databases, procedural manuals, organisational charts, protocols, and processes. According to a study, a conducive environment for knowledge sharing and innovation is fostered by strong SC, leading to improved organizational performance (33). Nonetheless, the impact of SC on operational efficacy is not always evident. Earlier research has hinted that the influence of SC on performance may be contingent upon supplementary factors, such as the quality of HC or the corporation's capability to effectively leverage its processes and systems. For instance, it was discovered that greater effectiveness in establishing strategic relationships and penetrating new markets was exhibited by companies with elevated levels of RC (34).

Relational Capital

RC, which denotes the value that is obtained from interactions with external stakeholders, is widely recognized as a significant aspect that shows a substantial role in determining a company's stance in the market and its long-term profitability. Numerous studies have shown that strong relational capital, characterized by trust, loyalty, and collaboration with customers and partners, can lead to enhanced market performance and competitive advantage. It was discovered that although supply chain performance might be improved by RC, rigidity and diminished flexibility may result if inadequately managed (35). The correlation between RC and performance is not consistently advantageous. Certain studies have underscored the potential drawbacks of relational capital, especially when it results in excessive dependence on particular relationships or when it is inadequately managed. Although supply chain performance could be improved by RC, rigidity and diminished flexibility could result if inadequately managed (36).

Null Hypothesis 4: RCE has no significant effect on a firm's market position or performance.

The VAIC™ Method: Evolution and Empirical Applications

The Development and Significance of the VAIC™ Method

The Value-Added Intellectual Coefficient (VAICTM) method, given by Ante Pulic in the late 1990s, offers a novel approach to quantifying IC and its effect on corporate success. VAICTM technique has three essential components that assess value creation efficiency: SC efficiency (SCE), HC efficiency (HCE), and capital employed efficiency (CEE). SCE reflects the role of SC in facilitating value development, HCE denotes the impact of the amount invested in HC, and CEE assesses the efficiency of financial and physical capital in creating worth. It enabled companies to assess the efficacy of their integrated circuit components and juxtapose their performance with industry standards. Initial empirical investigations utilizing VAIC™ exhibited its efficacy in elucidating the correlation between IC and FP. For example, it was found that variations in FP were significantly explained by VAIC™, particularly in knowledge-intensive industries (7, 37). However, while VAIC™ provided valuable insights into the efficiency of IC, it also faced criticism for its limited scope. Specifically, the original VAIC™ model did not account for relational capital, an increasingly recognized component of IC that includes associations with buyers, traders, and other external stakeholders. This limitation prompted scholars to seek extensions and modifications to the VAIC™ framework to better capture the full spectrum of IC.

The Extension to MVAIC: Incorporating Relational Capital

As an expansion of the original VAICTM model, researchers presented the modified VAIC (MVAIC) model in recognition of the necessity to account for relational capital. By adding a new element called RC Efficiency (RCE), which gauges how well a firm's external relationships produce value, the MVAIC model expands upon the VAICTM framework. The inclusion of RCE addresses the critique that the original VAIC™ overlooked the significance of external networks and partnerships, which are critical in today's interconnected and globalized business environment. Empirical studies using the MVAIC model have provided compelling evidence of its utility in capturing a more thorough portrayal of IC and its influence on FP. RC played a significant role in enhancing firm performance, particularly in service-oriented industries (38, 39). Further research reinforced these findings, with it being illustrated that a more sophisticated comprehension of IC's impact on FP was offered by MVAIC compared to the original

VAIC™(40).Also it examined firms across various industries in India, and showed that the inclusion of RCE significantly improved the explanatory power of the model, particularly in sectors where customer relationships and external networks are crucial. Since then, the MVAIC model has been widely used in IC research, especially in investigations aimed at comprehending the function of IC in certain sectors or geographical areas. For instance, the connection between IC and FP has been explored using the MVAIC model in recent years (41–43). These studies have consistently illustrated the importance of external relationships in the value-generation process by highlighting that relational capital, as defined by the MVAIC model, is a major determinant of creative performance.

Methodology and Measurement

Data Collection and Sampling

The study's data was obtained from the CMIE PROWESS Database of the National Stock Exchange (NSE) 500 index, which includes companies from several sectors. The period under review spans from 2014 to 2023. At first, a total of 317 companies were selected from the top NSE 500 corporations distributed among 7 industries. To maintain focus on industries where intellectual capital plays a distinct role, the sample excluded firms such as Oil, Gas and Consumable Fuels, metals construction materials, etc. Furthermore, companies exhibiting equity with a negative book value (BV), profit from negative operations, or lacking data on essential variables were also omitted. This encompasses situations where financial statements were not accessible, firms were temporarily or permanently halted, or companies were eliminated from the official listing (44). After applying these filters, the final sample consisted of 237 firms across 7 sectors as explained in Table 1.

Sector Classification of the Chosen Firms

Table 1: Firm Representation

Banks and Financial Services	67	31.28
IT	24	14.03
Consumer goods	51	11.83
Pharmaceutical	25	4.87
Automobile	21	4.60
Industrial manufacturing	36	2.41
Services	13	1.37
Total	237	70.39%

Variable and Measurements

Independent Variables (IV)

Numerous scholars have employed the VAIC model to assess the relationship between FP and IC efficiency in measuring intellectual capital (23, 45–49). To evaluate the effectiveness of IC, this study also makes use of the VAICTM methodology, which was established by Pulic (2000). The determination of a company's total value added is the first step in the process of computing the essential components of intellectual capital. This is how it is expressed: VA= W + I + T + NI (50). Where I = interest expenses; T = taxes paid; W = wages and salaries and NI = profit after tax. The second stage involves the calculation of the HC, SC, and capital employed (CE) for the following: HC = total wages and salary, SC = VA-HC, CE = capital employed (Capital employed = Total assets – Current liabilities.)

Finally, the calculation of VAIC and its three components:

- VAHU = VA/HC
- SCVA = SC/VA
- VACA= VA/CE.

Finally, VAIC = VACA + VAHU + SCVA

Where VAHU = Value-Added Human Capital, SCVA = Structural Capital Value Added, VACE = Value Added Capital Employed. The basic VAICTM method has been further developed by various scholars (51–55). By incorporating RC or HC as a new element into the model, now referred to as the MVAIC. A new component, relational capital, has been incorporated into MVAIC. Selling and distribution expenses are referred to as RC, which stands for "relational capital," and they are used to evaluate RCE, which stands for "RC efficiency." The implementation of RCE addresses the limitations that were present in earlier research conducted in India (56). To quantify the RC efficiency following formula is used:

VARCE = RC/VA; Thus, the complete formula is: MVAIC = VACA + VAHU + SCVA+VARCE

Dependent Variables (DV)

This analysis utilized three DV to account for their impact on firm performance

Return on Assets (ROA): This study employs ROA as the FP metric. A higher ROA indicates better asset efficiency and management (21, 28, 57–59). The formula for ROA is:

ROA= Net income / Total assets

Return on Equity (ROE): ROE evaluates the efficiency through which a corporation utilizes its shareholders' equity to produce a profit. A greater ROE means better profitability from the equity invested (20, 60). The formula for ROE is:

ROE = Net income / Shareholder's equity

Return on Capital Employed (ROCE): ROCE assesses a company's efficacy of producing profits from its utilized capital, which includes both equity and debt. This is a crucial indicator for assessing a company's sustained profitability. A higher ROCE indicates that the company is using its capital effectively (61–63).

ROCE = Operating income / Capital employed

Control Variables

Control variables are crucial in research models as they enable the isolation of IV influence on DV, considering other factors that may affect the outcome.

Firm Size

Definition: Assessed by total assets or revenue, often logged to normalize data. Used in various previous studies (24, 64). Consequently, the logarithm of year-end assets will serve as a proxy for size to mitigate this effect.

Firm Age

Definition: The duration in years since the firm's establishment (65).

Leverage

Leverage is calculated by Debt-to-Equity Ratio (DER) (51, 66, 67).

DER = Total debt / Shareholder's equity

Firm age, size, and debt-to-equity ratio (DER) as control variables are included in the study based on their well-established relevance in the literature. Age accounts for firm maturity, size captures economies of scale and market power, and DER reflects the financial structure, all of which are key determinants of firm performance. These variables effectively control for important firm characteristics while maintaining model parsimony.

Empirical Models

The hypotheses were evaluated utilizing both static and dynamic panel data regression models. Our dataset constitutes a balanced panel data structure. We employed both pooled ordinary least square (OLS) regression and Fixed Effect (FE) and Random Effect (RE) factor estimate practices to evaluate the influence of independent factors on different metrics of business performance utilizing STATA version 15. FE and RE models more accurately handle Unidentified effects and heterogeneity in the dataset compared to the basic Pooled OLS approach (56, 68). The rigorous Hausman specification test, introduced by Hausman (1978), was employed to ascertain suitable panel data regression model. If the null hypothesis is not rejected, the RE model is both efficient and consistent; in other scenarios, the FE model is preferable (14). We employed the dataset to estimate the ensuing empirical models. In a static panel data model, the connotations between the IV and DV are represented without accounting for any lagged dependent variable. The general form for the static model is:

Equation : ROA as Dependent Variable

$$ROA_{it} = \alpha + \beta 1MVAIC_{it} + \beta 2Age_{it} + \beta 3Size_{it} + \beta 4Leverage_{it} + \mu i + \epsilon it \quad [1]$$

Equation : ROE as Dependent Variable

$$ROE_{it} = \alpha + \beta 1MVAIC_{it} + \beta 2Age_{it} + \beta 3Size_{it} + \beta 4Leverage_{it} + \mu i + \epsilon it \quad [2]$$

Equation : ROCE as Dependent Variable

$$ROCE_{it} = \alpha + \beta 1MVAIC_{it} + \beta 2Age_{it} + \beta 3Size_{it} + \beta 4Leverage_{it} + \mu i + \epsilon it \quad [3]$$

Equations 4-6 will assess the correlation between the different elements of MVAIC and organizational performance:

Equation : ROA as Dependent Variable

$$ROA_{it} = \alpha + \beta 1VAHU_{it} + \beta 2VACA_{it} + \beta 3SCVA_{it} + \beta 4VARCE_{it} + \beta 5Age_{it} + \beta 6Size_{it} + \beta 7Leverage_{it} + \mu i + \epsilon it \ [4]$$

Equation : ROE as Dependent Variable

$ROE_{it} = \alpha + \beta 1VAHU_{it} + \beta 2VACA_{it} + \beta 3SCVA_{it} + \beta 4VARCE_{it} + \beta 5Age_{it} + \beta 6Size_{it} + \beta 7Leverage_{it} + \mu i + \epsilon it$ [5]

Equation: ROCE as Dependent Variable

$ROCE_{it} = \alpha + \beta 1VAHU_{it} + \beta 2VACA_{it} + \beta 3SCVA_{it} + \beta 4VARCE_{it} + \beta 5Age_{it} + \beta 6Size_{it} + \beta 7Leverage_{it} + \mu i + \epsilon it$ [6]

Dynamic Panel Data Models (DPDM)

For determining temporal persistence, a DPDM allows for the incorporation of the lagged DV as an IV. Static parameter estimation methods, as employed in Equations [1] – [6], may induce bias by neglecting the influence of historical performance, thus resulting in misleading findings. We used FE and RE parameter estimations in the preceding section. These estimations are only valid in situations where the performance of the present year is completely isolated from the performance of the preceding year (56). The Blundell and Bond (1998) two-step system GMM estimator is operated to address the endogeneity issue and guarantee robust outcomes (12, 69). The results of the GMM system estimator are only valid under the following conditions: the restriction established by the use of instruments is legitimate, and second-order autocorrelation is absent. The Sargen test is implemented in this investigation to assess the validity of the constraints imposed by the instruments utilized. The validity of the restrictions is delineated by the null hypothesis. In the second condition, the null hypothesis stated that there is no second-order autocorrelation, and second-order autocorrelation was analyzed. The validity and robustness of the GMM system (1998) estimator are inferred when the null hypothesis is not rejected for the sargan and second-order autocorrelation tests (70). The System GMM is sensitive to instrument proliferation, where using too many instruments can lead to overfitting, inefficient estimates, and unreliable. Another issue is the presence of weak instruments, which can result in biased and inconsistent estimates, particularly when the instruments are poorly correlated with the endogenous regressors. The computational complexity of the Two-Step System GMM estimator can be high, especially with large datasets or many instruments, making the estimation process time-consuming.As for alternative models, Difference GMM is another popular method that, like System GMM, deals with endogeneity (when variables are correlated with the error term), but it uses only past values of the variables as instruments. This can be simpler but less efficient when there are many periods.

Equation : ROA as Dependent Variable

$ROA_{it} = \alpha + \gamma ROA_{it-1} + \beta 1MVAIC_{it} + \beta 2Age_{it} + \beta 3Size_{it} + \beta 4Leverage_{it} + \mu i + \epsilon it$ [7]

Equation : ROE as Dependent Variable

$ROE_{it} = \alpha + \gamma ROE_{it-1} + \beta 1MVAIC_{it} + \beta 2Age_{it} + \beta 3Size_{it} + \beta 4Leverage_{it} + \mu i + \epsilon it$ [8]

Equation : ROCE as Dependent Variable

$ROCEit = \alpha + \gamma ROCE_{it-1} + \beta 1MVAIC_{it} + \beta 2Age_{it} + \beta 3Size_{it} + \beta 4Leverage_{it} + \mu i + \epsilon it$ [9]

Equation : ROA as Dependent Variable

$ROA_{it} = \alpha + \gamma ROA_{it-1} + \beta 1VAHU_{it} + \beta 2VACA_{it} + \beta 3SCVA_{it} + \beta 4VARCE_{it} + \beta 5Age_{it} + \beta 6Size_{it} + \beta 7Leverage_{it} + \mu i + \epsilon it$ [10]

Equation : ROE as Dependent Variable

$ROE_{it} = \alpha + \gamma ROE_{it-1} + \beta 1VAHU_{it} + \beta 2VACA_{it} + \beta 3SCVA_{it} + \beta 4VARCE_{it} + \beta 5Age_{it} + \beta 6Size_{it} + \beta 7Leverage_{it} + \mu i + \epsilon it$ [11]

Equation : ROCE as Dependent Variable

$ROCE_{it} = \alpha + \gamma ROCE_{it-1} + \beta 1VAHU_{it} + \beta 2VACA_{it} + \beta 3SCVA_{it} + \beta 4VARCE_{it} + \beta 5Age_{it} + \beta 6Size_{it} + \beta 7Leverage_{it} + \mu i + \epsilon it$ [12]

Results and Discussion

Correlation Matrix of Variables

Table 2: Correlation Matrix

Variable	ROE	ROCE	ROTA	VAHU	SCVA	VACE	VARCE	MVAIC	DER	Age	Size
ROE	1	0.515**	0.441**	-0.02	0.016	0.134**	0.04	-0.017	0.792**	-0.123**	-0.192**
ROCE	0.515**	1	0.887**	-0.111**	-0.009	0.286**	0.097**	-0.105**	0.011	-0.187**	-0.356**
ROTA	0.441**	0.887**	1	-0.109**	-0.02	0.218**	0.067**	-0.104**	-0.004	-0.219**	-0.387**
VAHU	-0.02	0.111**	-0.109**	1	0.305**	-0.042	-0.101**	1.000	0.022	0.067**	-0.038
SCVA	0.016	-0.009	-0.02	0.305**	1	-0.193**	-0.173**	0.305**	0.017	0.178**	0.330**
VACE	0.134**	0.286**	0.218**	-0.042	-0.193**	1	-0.04	-0.024	-0.006	-0.041	-0.152**
VARCE	0.04	0.097**	0.067**	-0.101**	-0.173**	-0.04	1	-0.094**	-0.007	-0.111**	-0.163**
MVAIC	-0.017	-0.105**	-0.104**	1	0.305**	-0.024	-0.094**	1	0.022	0.066**	-0.037
DER	0.792**	0.011	-0.004	0.022	0.017	-0.006	-0.007	0.022	1	-0.016	-0.013
AGE	-0.123**	-0.102**	-0.160**	-0.037	0.097	-0.039	0.089**	-0.037	-0.016	1	0.317**
SIZE	-0.192**	-0.356**	-0.387**	0.201**	0.330**	-0.152**	-0.163**	0.199**	-0.013	0.317**	1

Significant at 1% Level: ** ($p < 0.01$)

Table 2 presents correlation matrix of all variables. The independent variables—MVAIC, VAHU, SCVA, VACE, VARCE, DER, AGE, and LOGTA—exhibit various significant relationships with the dependent variables ROE, ROCE, and ROTA, highlighting their influence on a firm's FP. MVAIC shows a slight negative correlation with ROE, ROCE, and ROTA, indicating that while intellectual capital is crucial, its impact on these specific performance metrics might be subtle or dependent on other factors. VAHU is slightly negatively correlated with ROE and ROTA, suggesting that while HC is valuable, it may not directly enhance returns on equity or assets. However, it correlates with ROCE, reflecting its potential value. SCVA exhibits a moderate favorable relationship with return on equity and a modest unfavourable correlation with ROCE and ROTA. This indicates that as firms increase their SC, they may experience higher total assets, but this does not necessarily translate to better returns on capital or assets. VACE shows a positive relationship with all three-performance metrics, particularly ROCE and ROTA, suggesting that efficient capital utilization is key to achieving strong financial returns. VARCE exhibits significant positive associations with ROCE and ROTA, indicating that investment in research capital contributes positively to the firm's returns on capital and assets. Also, DER has a strong link with Return on Equity (ROE), underscoring the essential function of a balanced capital structure in augmenting net worth returns. AGE exhibits a marginal negative association with ROE, ROCE, and ROTA, indicating that as enterprises mature, their returns may somewhat decline, possibly due to the difficulties older firms encounter in sustaining growth. LOGTA (Log of Total Assets) exhibits a negative correlation with all three dependent variables, suggesting that as enterprises increase in asset size, they may encounter declining returns on net worth, capital employed, and assets. Nonetheless, this will not result in any multicollinearity issues, as these variables are employed in two distinct regression models. Consequently, the issue of multicollinearity is absent in the data during the execution of panel regression analysis.

Test of Stationarity

Table 3: Test of Stationarity (Unit Root Test)

Type of variables	Name of Variables	LLC stats	P value	Remark
Dependent	ROE	-220	0.000	Stationary
Dependent	ROCE	-35.129	0.000	Stationary
Dependent	ROTA	-38.486	0.000	Stationary
Independent	VAHU	-50.766	0.000	Stationary
Independent	SCVA	-59.501	0.000	Stationary
Independent	VACE	-93.463	0.000	Stationary
Independent	VARCE	-580	0.000	Stationary
Independent	MVAIC	-53.05	0.000	Stationary

Control	DER	-1.2	0.000	Stationary
Control	Log TA	-60.947	0.000	Stationary

The results shown on table 3 are of the Levin, Lin, and Chu (LLC) test indicate that all the dependent variables ROTA, ROE, and ROCE—are stationary, as evidenced by their highly significant LLC statistics and p-values of 0.000. This indicates that these variables lack a unit root, signifying that their statistical characteristics, including mean and variance, stay stable across time. Similarly, the independent variables, including VAHU, SCVA, VACE, VARCE, and MVAIC, as well as the control variables DER and Log TA, are also stationary with significant LLC statistics and p-values of 0.000. The stationarity of these variables ensures their suitability for regression models, resulting in precise and reliable conclusions in examining the relationship between IC efficiency and FP.

Panel Regression Results

Table 4 displays the regression outcomes from many models—Pooled OLS regression, (RE), Fixed Effects (FE), and System GMM—examining the correlation between IC and FP, quantified by Return on Equity (ROE). Essential variables comprise MVAIC, VAHU (HC Efficiency), SCVA (SC Efficiency), VACE, VARCE, DER (Debt-to-Equity ratio), Age, and the Size (log TA). Preference for Fixed Effects model over Random Effects. The findings indicate that MVAIC is significant in the System GMM model, demonstrating a positive yet context-dependent effect on ROE, and is significant at the 10% level in the random effects model. The inclusion of the lag of ROE in the System GMM model indicates the dynamic nature of firm performance, where past performance (ROE in the previous period) significantly influences current ROE. The substantial and statistically significant coefficient of the lagged ROE variable (0.0492 and 0.0511 in the two System GMM models) indicates that firms with elevated ROE in the preceding period are likely to sustain or enhance their performance in the present era. HC Efficiency (VAHU) shows a negative relationship with ROE in the Pooled OLS and RE models but is insignificant in the System GMM model, suggesting its limited direct impact on performance. SC (SCVA), (VACE) and VARCE (new variable) consistently shows great and favourable effect on ROE across all models, highlighting their importance in driving firm performance. DER shows a robust great association of ROE across all estimations, while firm size (Log TA) negatively impacts performance, indicating that larger firms might face diminishing returns. Age has mixed results, showing negative effects in OLS and RE models but positive effects in the System GMM model. The Wald test and F-test are both used in analysis to verify the significance of the IV and the overall model fit which is significant across all models signifying overall model fit. The Hausman test supports the use of the FE model over RE, while the absence of AR (2) autocorrelation (p value >0.05) and Sargan test (p value >0.05) which indicates that the instruments are valid suggest that the System GMM results are valid and robust. The R-squared values 66.39%, 68.66%, 66.33%, and 48.73% show that the study's utilization of intellectual capital and other control factors, as determined by the Pooled OLS, FE, and RE panel regression approaches, explained variances in the performance of all organizations. These high R-squared values indicate that the models provide a strong fit, with IC and control variables effectively explaining the majority of performance differences among the firms, though with slight variability depending on the regression method applied.

Table 4: Dependent Variable ROE: Static and Dynamic Panel Regression Results

Variables	Pooled OLS	Pooled OLS	Random Effects (RE)	Fixed effects (FE)	System GMM	System GMM
Lag of ROE					.0492 (8.53**)	.0511(7.96**)
Constant	42.068 (22.59**)	27.499 (12.44**)	42.401 (13.25**)	-25.486 (-4.07**)	65.38(10.61**)	
MVAIC	-0.004 (-0.36)		0.0186 (1.31*)		0.62(2.05**)	
VAHU		-0.027(-2.33**)		-0.008(-0.59**)		-.00044(-0.07)
SCVA		16.230 (7.80**)		45.272 (12.61**)		41.06(10.84**)

VACE		6.276 (10.64**)		16.151 (12.93**)		23.68(6.94**)
VARCE		4.529(3.68**)		4.142 (2.27**)		0.8122(0.53)
DER	1.140 (63.05**)	1.140 (65.22**)	1.143 (77.41**)	1.139 (94.05**)	1.15(336.13**)	1.14(429.66**)
Age	-0.065 (-4.47**)	-0.076(-5.38**)	-0.061 (-2.07**)	0.368 (2.73**)	.88(5.99**)	0.341(2.68**)
Size (log TA)	-2.616 (-11.97**)	-2.595(-11.63**)	-2.705 (-7.34**)	-1.7(-2.58**)	-10.10(-9.02**)	-1.18(-1.11)
R Square	66.39%	68.66%	66.33%	48.73%		
F stat / Wald test	1059.33**	670.77**	6148.33**	1101**	13609.21**	868290.80**
Hausman test			2.44 (0.654)	115.06** (0.000)		
Sargan Test (p-value)					0.076	0.09
AR (1)- Serial autocorrelation (p-value)					0.0008	0.0000
AR (2)-Serial autocorrelation (p-value)					0.0377	0.2646

Note: The significance level is shown at **p<0.05, *p<0.10, Lag of ROE shows the one-year logged values dependent variable (ROE).

Table 5: Dependent Variable ROA: static and Dynamic Panel Regression Results

Variables	**Pooled OLS**	**Pooled OLS**	**Random Effects (RE)**	**Fixed Effects (FE)**	**System GMM**	**System GMM**
Lag of ROA					0.522(27.13**)	0.335(17.01**)
Constant	23.502 (30.28**)	17.789 (19.24**)	19.982 (14.87**)	-14.795 (−7.67**)	8.50(3.63**)	-22.76(-6.52**)
MVAIC	-0.008(-1.61)		0.0121 (2.37**)		0.018(1.18)	
VAHU		-0.019(-3.77**)		0.0011 (0.24)		-0.0018(-0.26)
SCVA		7.180 (8.25**)		22.0838 (19.95**)		18.58(9.80**)
VACE		2.380 (9.65**)		5.3043 (13.77**)		7.888(4.54**)
VARCE		1.071 (2.08*)		0.1463 (0.26*)		0.0066(4.59**)
DER	-0.003 (-0.45)	-0.004(-0.51)	0.0019 (0.39)	0.0006 (0.14)	0.004(3.49**)	-0.030(-0.41)
Age	-0.013(-2.16*)	-0.017(-2.78**)	-0.0036 (-0.25)	0.3119 (7.49**)	0.076(1.39)	1.43(2.35**)
Size (log TA)	-1.553(17.04**)	-1.595(-17.08**)	-1.2338 (-8.06**)	-0.9365 (−4.54**)	-0.9133(3.63**)	-22.76(-6.52**)
R Square	15.25%	20.43%	14.24%	30.71%		
F stat /Wald test	96.55**	78.60**	80.81**	120.62**	836.24**	1064.40**
Hausman test			5.90 (0.2067)	560.25** (0.0000)		
Sargan test (p-value)					0.065	0.10
AR (1)-Serial autocorrelation (p value)			0.121** (0.0480)		0.000	0.0003
AR (2)-Serial autocorrelation			0.1784 (0.521)		0.165	0.2593

(p-value)

Note: The significance level is shown at **p<0.05, *p<0.10, Lag of ROA shows the one year logged values dependent variable (ROA).

This table 5 presents the results of multiple regression models—Pooled OLS, Random Effects, Fixed Effects, and System GMM—analysing the relationship between various IC components and ROA. The significant coefficient for lag **of** ROA in both System GMM models underscores the dynamic persistence of FP, affirming that past profitability exerts a substantial influence on present outcomes, a phenomenon widely acknowledged in corporate finance literature. In terms of intellectual capital, MVAIC demonstrates statistical significance in the RE model but loses prominence in the System GMM model, suggesting a nuanced, context-dependent effect on firm profitability (71). SCVA (SC Value Added) and VACE maintain robust, positive impacts across all models, reinforcing the centrality of organizational infrastructure and efficient capital allocation in driving superior FP. Conversely, VAHU (HC Efficiency) displays inconsistencies, with VAHU showing a negative impact in the Pooled OLS model and insignificant results in System GMM, indicating its limited direct influence on profitability, while VARCE (RC Efficiency) is positively significant at a 10% level. Control variables such as Firm Size (Log TA) consistently exhibit a negative correlation with ROA, suggesting the diminishing returns experienced by larger firms, while Age displays mixed results, showing negative significance in OLS however a positive influence in the FE and System GMM models. The Wald test and F-test are both used to assess the significance of the IV and the overall model fit. Moreover, the absence of significant second-order autocorrelation AR [2] and Sargan test (p value >0.05) which indicates that the instruments are valid validates the robustness of the System GMM estimations, ensuring the precision and reliability of the model. The complex interaction between elements of IC and FP indicates that, whereas structural and capital efficiency are primary determinants of profitability, other factors like HC may exert more inconsistent influences. The R-squared values of 15.25%, 20.43%, 14.24%, and 30.71% suggest that the independent variables, including Intellectual Capital (MVAIC) and control variables such as DER, firm age, and firm size, explain a moderate portion of the variability in company performance across different model specifications.

Table 6: Dependent Variable ROCE: Static and Dynamic Panel Regression Results

Variables	**Pooled OLS**	**Pooled OLS**	**Random Effects (RE)**	**Fixed effects (FE)**	**System GMM**	**System GMM**
Lag of ROCE					0.65(33.04**)	.4289(11.83**)
Constant	35.682 (27.13**)	23.432 (15.30**)	23.261 (7.15**)	-14.795 (−7.67**)	-1.26(-0.33)	-37.43(-6.31**)
MVAIC	-0.014 (-1.68)		0.0262 (2.81**)		0.021(1.08)	
VAHU		-0.033 (-4.07**)		0.0011 (0.24)		0.005(-0.75)
SCVA		13.283 (9.21**)		22.0838 (19.95**)		24.41(8.96**)
VACE		5.631 (13.78**)		5.3043 (13.77**)		12.48(4.58**)
VARCE		3.322 (3.90**)		0.1463 (0.26)		0.761(0.69)
DER	0.004 (0.34)	0.004 (0.35)	0.0176 (2.07**)	0.0006 (0.14)	0.035(18.50**)	0.03(9.48**)
Age	0.004 (0.40)	-0.005 (-0.50)	0.1579 (1.91)	0.3119 (7.49**)	-.117(-2.51**)	-.264(-2.16**)
Size (log TA)	-2.494 (-16.15**)	-2.462 (-15.91**)	-1.9331 (-4.70**)	-0.9365 (−4.54**)	1.166(1.97**)	3.66(3.19**)

R Square	12.83%	21.73%	27.1%	33.98%		
F stat / Wald test	78.99**	85.02**	9.43**	140.09**	1799.83**	713.55**
Hausman test			17.18 (0.0018)	272.38**(0.0000)		
Sargan test(p-value)					0.059	0.055
AR (1)-Serial autocorrelation (p-value)					0.000	0.000
AR (2)-Serial autocorrelation (p-value)					0.125	0.332

Note: The significance level is shown at **p<0.05, *p<0.10, Lag of ROCE shows the one-year logged values dependent variable (ROCE)

The table 6 encapsulates an intricate examination of the determinants of Return on Capital Employed (ROCE) through a series of models—Pooled OLS, RE, FE, and System GMM—offering granular insights into the dynamic interplay between IC components and FP. Notably, the lag of ROCE emerges as profoundly significant in both System GMM models, with coefficients of 0.65 and 0.4289, respectively, signifying a considerable temporal persistence in ROCE. This underscores the self-reinforcing nature of capital efficiency, wherein past profitability significantly influences future performance, corroborating findings from prior empirical studies on the inertia of corporate financial metrics. The MVAIC reports significance in the RE model, indicating that intellectual capital exerts a favorable influence on ROCE, albeit the impact is diminished or statistically insignificant in GMM model, suggesting that the effect of intellectual capital on ROCE might be contextually constrained or dependent on other firm-specific factors. Among the individual intellectual capital components, SCVA (SC Value Added) and VACE exhibit robust and highly significant positive coefficients across all models, denoting that firms with more efficient structural and capital-employed management tend to exhibit superior returns on capital employed. These outcomes are constant with intellectual capital theory, which emphasizes the critical role of organizational structures and capital utilization in creating value and enhancing profitability. On the contrary, VAHU (HC Efficiency) demonstrates a negative and significant coefficient in the Pooled OLS model, hinting at potential inefficiencies in HC investments relative to value creation in some firms. Similarly, VARCE shows modest or non-significant effects across most models except OLS, suggesting a limited direct contribution of RC to ROCE, potentially reflecting sector-specific dependencies or the intangible nature of relational assets. Control variables provide further nuance. The DER shows a consistently positive relationship with ROCE, particularly in the System GMM model, signifying that firms leveraging more debt relative to equity may enhance their capital efficiency. However, firm age yields mixed results, revealing a negative coefficient in the System GMM models, indicating that older firms might face declining returns on capital due to aging infrastructure or market obsolescence. Lastly, firm size (Log TA) is negatively correlated with ROCE in most models, suggesting that larger firms may experience diminishing returns due to increased operational complexities and inefficiencies. The importance of the Wald test across models highlights the general reliability of the estimations. The absence of significant AR [2] serial autocorrelation Sargan test (p value >0.05) confirms the dependability of the GMM estimates, guaranteeing that the instrument set employed in the estimation process is legitimate and uncorrelated with the error term, hence enhancing the confidence of the results. The R-squared values of 12.83%, 21.73%, 27.1%, and 33.98% suggest that the independent variables, including Intellectual Capital (MVAIC) and control variables such as DER, firm age, and firm size, explain a moderate portion of the variability in company performance across different model specifications.

Conclusion

Indicators of FP and its relationship to intellectual capital—namely ROA, ROE, and ROCE highlight many key areas for improvement and strategic focus. The findings demonstrate that IC positively influences ROE, ROCE, and ROA (44, 57, 60, 72, 73). Specifically, SCVA and VACE show substantial positive results which shows companies can drive better FP across these metrics (21, 73). Also, the influence of VAHU is not substantial, but the influence of VARCE is significant for ROA and ROE (51, 67) which suggests that companies that prioritize the development and preservation of robust relational networks can achieve superior financial results. To completely translate into measurable financial gains, the impact of HC, while essential, must be complemented by other factors such as strong organizational structures, effective management practices, or relational capital. Organizations should therefore ensure that their HC investments are strategic and targeted to foster skills that directly contribute to FP. Overall, VACE, SCVA, and VARCE are determined to be the primary value-added drivers. In improving ROCE, the significant positive effects of SCVA and VACE underscore the importance of enhancing structural and capital-employed efficiencies. Firms should adopt best practices in managing their physical and financial resources to maximize returns on capital employed. This includes optimizing investment in physical assets and ensuring effective use of capital.

Economic Significance and Policy Implication of the Findings

The estimated effects of IC and FP are practically meaningful for firms, especially when considering the broader components of IC, such as **structural** and relational capital. While human capital may not have a direct, significant impact, the findings suggest that investments in organizational processes, intellectual property, technological advancements, and strong relationships with customers and partners can drive substantial improvements in firm performance. These components of IC are key to enhancing productivity, fostering innovation, and achieving competitive advantages, which ultimately contribute to higher profitability, market share, and long-term sustainability. Firms that strategically build and leverage their intellectual capital are more likely to experience improved productivity, innovation, and ultimately higher profitability, making the estimated effects of IC highly relevant and practically meaningful for business strategy. From a policy perspective, the results indicate the need for policymakers to support educational programs that enhance human capital and create incentives for R&D and innovation. Additionally, promoting a favorable regulatory environment for intellectual property can help firms protect their innovations and improve their competitive edge. **Investors** can leverage these findings by prioritizing firms with strong IC in their portfolios, while **firms** can adopt targeted strategies to enhance their intellectual capital, ensuring long-term growth and sustained performance improvements. Ultimately, these findings suggest that investment in IC is not only essential for firm success but also a key driver of broader economic development.

Limitations and Future Research Scope of the Study

The present study utilizes the MVAIC model, while valuable in linking intellectual capital (IC) to firm performance (FP), has limitations due to its reliance on financial data (quantitative), which tends to overlook non-financial aspects(qualitative) of IC. Also, it relies heavily on market value, which can be volatile and may not fully reflect the intangible aspects of IC, particularly in industries where market value does not align with the true value of intellectual assets. So the other alternative methods such as the Skandia Navigator model offers a holistic approach by incorporating multiple strategic perspectives (financial, customer, process, and renewal), allowing for a broader view of IC's role in business strategy and the Intellectual Capital Benchmark model which is particularly useful for benchmarking, enabling comparisons across firms and industries to identify gaps and best practices in IC management. Furthermore, the study analyses the impact of IC of firms under seven industries as a whole, a cross-industry comparison can also be conducted. Also the firms under study are based in India, Future research could expand the sample size and consider cross-industry and cross-country comparisons. This could provide deeper insights into how the impact of IC varies across different sectors and countries, as the role of IC may differ depending on industry characteristics and the types of intellectual assets prevalent in each sector and country. Different models such as Skaindia navigator, Balance scorecard etc. can be used to calculate IC to capture all the aspect i.e quantitative and qualitative. Also, exploring the role of external factors, such as institutional frameworks, government policies, or cultural influences, in shaping the development and impact of intellectual capital could be valuable. Understanding how external conditions affect IC could help inform policy recommendations and business strategies aimed at enhancing the value of intellectual capital.

Abbreviations

IC: Intellectual capital, HC or HCE: Human capital or Human capital efficiency, SC or SCE: Structural capital or Structural capital efficiency, RC or RCE: Relational Capital or Relational capital efficiency, FP: Financial performance VA: value Added, VAIC or MVAIC: Value added intellectual capital or modified value-added intellectual capital, DPDM: Dynamic Panel Data Models, FE or RE: Fixed Effect or Random Effect, AR: Autocorrelation, GMM: Generalized Method of Moments, DV: Dependent variable, TA: total assets, ROA: Return on asset, ROE: Return on equity, ROCE: Return on Capital employed, DER: Debt To Equity Ratio, OLS: Ordinary Least Square.

Acknowledgement

The authors would like to express their gratitude to the Department of Commerce, Chaudhary Devi Lal University for providing a better research environment to conduct the study and in completing this research.

Author Contributions

Anchal Bansal have conceptualized and designed the study, also collected data for the study and Priya Bansal and Prof Silender Singh made substantial contributions to the statistical analysis and interpretation of data. All three authors have critically reviewed the content and approved its submission to the Journal.

Conflict of Interest

We would like to disclose that there are no apparent or actual conflicts of interest related to this manuscript for any of the listed authors.

Ethics Approval

Not Applicable.

Funding

This research received no funding.

References

1. Edvinsson L. Developing intellectual capital at Skandia. Long Range Planning. 1997;30(3):366-373.
2. Stewart T, Ruckdeschel C. Intellectual capital: The new wealth of organizations. Performance Improvement. 1998 Sep;37(7):56-59.
3. Bontis N. Assessing knowledge assets: A review of the models used to measure intellectual capital. International Journal of Management Reviews. 2001;3(1):41-60.
4. Barney J. Firm resources and sustained competitive advantage. Journal of Management. 1991;17(1):99-120.
5. Pulic A. Intellectual capital – does it create or destroy value? Measuring Business Excellence. 2004 Mar 1;8(1):62-68.
6. Sveiby KE. The New Organizational Wealth: Managing and Measuring Knowledge-Based Assets. San Francisco: Berrett-Koehler; 1997. 275 p. Available from: https://www.academia.edu/27198566/The_New_Organizational_Wealth_Managing_and_Measuring_Knowledge_Based_Assets_Karl_Erik_Sveiby_Berrett_Koehler_San_Fransisco_1997_275_pp
7. Chen MC, Cheng SJ, Hwang Y. An empirical investigation of the relationship between intellectual capital and firms' market value and financial performance. Journal of Intellectual Capital. 2005 Jun 1;6(2):159-176.
8. Ting IWK, Lean HH. Intellectual capital performance of financial institutions in Malaysia. Journal of Intellectual Capital. 2009 Oct 16;10(4):588-599.
9. Clarke M, Seng D, Whiting RH. Intellectual capital and firm performance in Australia. Journal of Intellectual Capital. 2011 Oct;12(4):505-530.
10. Sveiby KE. The intangible assets monitor. Journal of Human Resource Costing and Accounting. 1997;2(1):73-97.
11. Guthrie J, Ricceri F, Dumay J. Reflections and projections: A decade of intellectual capital accounting research. British Accounting Review. 2012 Jun;44(2):68-82.
12. Arellano M, Bond S. Another look at the instrumental variable estimation of error-components models. Journal of Econometrics. 1995;68(1):29-51.
13. Wintoki MB, Linck JS, Netter JM. Endogeneity and the dynamics of internal corporate governance. Journal of Financial Economics. 2012 Sep;105(3):581-606.
14. Soetanto T, Liem PF. Intellectual capital in Indonesia: Dynamic panel approach. Journal of Asia Business Studies. 2019 Mar 21;13(2):240-262.
15. Mohammad SH, Bujang I. Performance of Malaysian financial firms: An intellectual capital perspective using MVAIC model. Asian Economic and Financial Review. 2019 Oct 26;9(7):752-765.
16. Majumder SC, Appiah BK, Cardorel OC. Determinants of market to book value and financial performance of Chinese listed firms: Implication of MVAIC model. International Journal of Learning and Intellectual Capital. 2021;18(2):131-153.
17. Bontis N. Intellectual capital: An exploratory study that develops measures and models. Management Decision. 1998;36(2):63-76.
18. Wang Z, Cai S, Liang H, Wang N, Xiang E. Intellectual capital and firm performance: The mediating role of innovation speed and quality. International Journal

of Human Resource Management.2021;32(6):1222-1250.
19. Lestari B, Akuntansi AS. Firm's value exploration: The impact of intellectual capital and net working capital. Jurnal Dinamika Akuntansi . 2020 Nov 24;12(2):152-164.
20. Soewarno N, Hilal A, Ramadhan A. The effect of ownership structure and intellectual capital on firm value with firm performance as an intervening variable. International Journal of Innovation, Creativity and Change. 2020 Oct ;10(12):215-236.
21. Joshi M, Cahill D, Sidhu J, Kansal M. Intellectual capital and financial performance: An evaluation of the Australian financial sector. Journal of Intellectual Capital. 2013 Apr;14(2):264-285.
22. Weqar F, Khan AM, Haque SMI. Exploring the effect of intellectual capital on financial performance: A study of Indian banks. Measuring Business Excellence.2020 Nov;24(4):511-529;
23. Gupta K, Goel S, Bhatia P. An analysis of intellectual capital and firms' profitability: With reference to Indian IT companies. NMIMS Management Review 2019 Sep; 37(2):77-91.
24. Tan HP, Plowman D, Hancock P. Intellectual capital and financial returns of companies. Journal of Intellectual Capital. 2007;8(1):76-95.
25. Pucci T, Simoni C, Zanni L. Measuring the relationship between marketing assets, intellectual capital and firm performance. Journal of Management and Governance. 2015 Aug;19(3):589-616
26. Andriani LA, Herlina E. The effect of intellectual capital on financial performance and market value of manufacturing companies listed in the Indonesia Stock Exchange 2010-2012. The Indonesian Accounting Review. 2015;5(1):45–54.
27. Mehralian G, Rasekh HR, Akhavan P, Sadeh MR. The impact of Intellectual capital efficiency on market value: An empirical study from Iranian pharmaceutical companies. Iranian Journal of Pharmaceutical Research. 2012;11(1):195–207.
28. Maditinos D, Chatzoudes D, Tsairidis C, Theriou G. The impact of intellectual capital on firms' market value and financial performance. Journal of Intellectual Capital. 2011 Jan;12(1):132-151.
29. Youndt MA, Subramaniam M, Snell SA. Intellectual capital profiles: An examination of investments and returns. Journal of Management Studies. 2004 Mar;41(2):335-361.
30. Crook TR, Todd SY, Combs JG, Woehr DJ, Ketchen DJ. Does human capital matter? A meta-analysis of the relationship between human capital and firm performance. Journal of Applied Psychology. 2011 May;96(3):443-456.
31. Selvarajan TT, Ramamoorthy N, Flood PC, Guthrie JP, MacCurtain S, Liu W. The role of human capital philosophy in promoting firm innovativeness and performance: Test of a causal model. International Journal of Human Resource Management. 2007 Aug;18(8):1456–70.
32. Xu J, Wang B. Intellectual capital, financial performance and companies' sustainable growth: Evidence from the Korean manufacturing industry. Sustainability. 2018 Dec 6;10(12):1-15.
33. Inkinen H. Review of empirical research on intellectual capital and firm performance. Journal of Intellectual Capital. 2015 Jul 13;16(3):518–65.
34. Roos G, Pike S, Fernström L. Managing intellectual capital in practice. Managing Intellectual Capital in Practice. Taylor and Francis. 2007; p.1–384. Available from: https://www.taylorfrancis.com/books/mono/10.4324/9780080479118/managing-intellectual-capital-practice-stephen-pike-g%C3%B6ran-roos-lisa-fernstrom-g%C3%B6ran-roos
35. Kale P, Singh H, Perlmutter H. Learning and protection of proprietary assets in strategic alliances: Building relational capital. Strategic Management Journal. 2000;21(3):217–37.
36. Villena VH, Revilla E, Choi TY. The dark side of buyer-supplier relationships: A social capital perspective. Journal of Operations Management. 2011;29(6):561–76.
37. Firer S, Williams SM. Intellectual capital and traditional measures of corporate performance. Journal of Intellectual Capital. 2003 Sep 1;4(3):348–60.
38. Nazari JA, Herremans IM. Extended VAIC model: Measuring intellectual capital components. Journal of Intellectual Capital. 2007;8(4):595–609.
39. Pulic A. VAICTM – An accounting tool for intellectual capital management. International Journal of Technology Management. 2000; 20:702–714.
40. Smriti N, Das N. The impact of intellectual capital on firm performance: A study of Indian firms listed in COSPI. Journal of Intellectual Capital. 2018 Aug 31;19(5):935–64.
41. Maji SG, Goswami M. Intellectual capital and firm performance in India: A comparative study between original and modified value-added intellectual coefficient model. International Journal of Learning and Intellectual Capital. 2017;14(1):76–89.
42. Restuti MD, Diyanty V, Shauki ER. Intellectual capital and firm Performance: Applying a modified Value-Added Coefficient. Advances in Economics, Business and Management Research. Atlantis Press; 2018. p. 114–23.
Available from: https://www.atlantis-press.com/proceedings/apbec-18/125913749
43. Ulum I, Kharismawati N, Syam D. Modified value-added intellectual coefficient (MVAIC) and traditional financial performance of Indonesian biggest companies. International Journal of Learning and Intellectual Capital. 2017 Nov 24;14(3):207–19.
44. Zéghal D, Maaloul A. Analysing value added as an indicator of intellectual capital and its consequences on company performance. Journal of Intellectual Capital. 2010 Jan;11(1):39–60.
45. Kamath GB. An investigation into intellectual capital efficiency and export performance of firms in India. International Journal of Learning and Intellectual Capital. 2017;14(1):47–75.
46. Onumah JM, Duho KCT. Impact of intellectual capital on bank efficiency in emerging markets: Evidence from Ghana. International Journal of Banking, Accounting and Finance. 2020;11(4):435–60.
47. Kweh QL, Ting IWK, Hanh LTM, Zhang C. Intellectual capital, governmental presence, and firm performance of publicly listed companies in

Malaysia. International Journal of Learning and Intellectual Capital. 2019;16(2):193–211.
48. Shaban M, Kavida V. Intellectual capital, financial performance and market valuation: An empirical investigation of Information Technology industry in India. Asia-Pacific Journal of Management Research and Innovation. 2013;9(1):55–62.
49. Kavida V. Impact of intellectual capital efficiency on firm performance, CAPM expected return and value at risk of IT MNCs in India. Mukt Shabd Journal. 2020 Nov 24;9(6):1637–62.
50. Singh RD, Narwal KP. Intellectual capital and its consequences on company performance: A study of Indian sectors. International Journal of Learning and Intellectual Capital. 2015;12(3):300–22.
51. Tiwari R. Nexus between intellectual capital and profitability with interaction effects: panel data evidence from the Indian healthcare industry. Journal of Intellectual Capital. 2020;21(5):733-58.
52. Vishnu S, Gupta VK. Intellectual capital and performance of pharmaceutical firms in India. Journal of Intellectual Capital. 2014;15(1):83-99.
53. Xu J, Li J. The interrelationship between intellectual capital and firm performance: evidence from China's manufacturing sector. Journal of Intellectual Capital. 2020 Feb 8;23(2):313-41.
54. Mukherjee T, Sen SS. Intellectual Capital and Corporate Sustainable Growth: The Indian Evidence. Journal of Business Economics and Environmental Studies. 2019 Apr 30;9(2):5-15.
55. Faruq MO, Akter T, Mizanur Rahman M. Does intellectual capital drive bank's performance in Bangladesh? Evidence from static and dynamic approach. Heliyon. 2023 Jul 1;9(7):18121.
56. Gan K, Saleh Z. Intellectual capital and corporate performance of technology-intensive companies: Malaysia evidence. Asian Journal of Business and Accounting. 2008 Jun 30;1(1):113-30.
57. Nimtrakoon S. The relationship between intellectual capital, firms' market value and financial performance: empirical evidence from the ASEAN. Journal of Intellectual Capital. 2015 Jul 13;16(3):587-618.
58. Gopal S, Goswami MM. Intellectual capital and firm performance in emerging economies: The case of India. Review of International Business and Strategy. 2016;26(3):373-86.
59. Chu SKW, Chan KH, Wu WWY. Charting intellectual capital performance of the gateway to China. Journal of Intellectual Capital. 2011 Apr;12(2):249-76.
60. Holienka M, Pilková A, Kubišová M. The influence of intellectual capital performance on value creation in Slovak SMEs.The Essence and Measurement of Organizational Efficiency. Switzerland: Springer International Publishing; 2016. p. 65–77. Available from: https://link.springer.com/chapter/10.1007/978-3-319-21139-8_5
61. Nedelcu AC, Banacu CS, Frasineanu C. The Impact of Intellectual Capital on Automotive Firm's Performance-Case Study.Management Challenges for Sustainable Development. Bucharest, Romania; 2014. p. 703-17. Available from: http://www.business24.ro/auto/piata-auto/industria-auto-motorul-cresterii-
62. Mohapatra S, Pattanayak JK. Unraveling the Dynamics of Intellectual Capital, Firm Performance, and the Influential Moderators—BIG4 Auditors and Group Affiliation. International Journal of Financial Studies. 2024 Mar 1;12(1):1-29.
63. Kamaluddin A, Rahman RA. Intellectual capital: Definitions, categorization and reporting models. Journal of Intellectual Capital. 2008;9(4):609-38.
64. Mariana Taliyang S, Sultan Zainal Abidin Rohaida Abdul Latif U, Utara Malaysia Nurul Huda Mustafa U, Sultan Zainal Abidin U. The determinants of intellectual capital disclosure among Malaysian listed companies. International Journal of Management and Marketing Research. 2011;4(3):25-33.
65. Pal K, Soriya S. IC performance of Indian pharmaceutical and textile industry. Journal of Intellectual Capital. 2012 Jan;13(1):120-37.
66. Xu J, Wang B. Intellectual Capital Performance of the Textile Industry in Emerging Markets: A Comparison with China and South Korea. Sustainability. 2019;11(8):2354.
67. Oppong GK, Pattanayak JK. Does investing in intellectual capital improve productivity? Panel evidence from commercial banks in India. Borsa Istanbul Review. 2019 Sep 1;19(3):219-27.
68. Blundell R, Bond S. Initial conditions and moment restrictions in dynamic panel data models. Journal of Econometrics. 1998;87:115-43.
69. Sardo F, Serrasqueiro Z. Intellectual capital, growth opportunities, and financial performance in European firms: Dynamic panel data analysis. Journal of Intellectual Capital. 2018 Jul 10;19(4):747-67.
70. Olarewaju OM, Msomi TS. Intellectual capital and financial performance of South African development community's general insurance companies. Heliyon. 2021 Apr 1;7(4):06949.
71. Dženopoljac V, Janoševic S, Bontis N. Intellectual capital and financial performance in the Serbian ICT industry. Journal of Intellectual Capital. 2016 Apr 11;17(2):373-96.
72. Nadeem M, Gan C, Nguyen C. The importance of intellectual capital for firm performance: Evidence from Australia. Australian Accounting Review. 2018 Sep 1;28(3):334-44.
73. Nadeem M, Gan C, Nguyen C. Does intellectual capital efficiency improve firm performance in BRICS economies? Dynamic panel estimation. Measuring Business Excellence. 2017;21(1):65-85.