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Intellectual Capital Efficiency and Firm Life Cycle Dynamics for Productivity and Resilience in Emerging Economies

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Abstract

The current study benchmarks intellectual capital efficiency across firm life cycle stages and examines its role as a strategic driver of firms' life cycle dynamics. Building on life cycle theory and the resource-based view, it examines variations in efficiency across life cycle stages and evaluates how intellectual capital utilization shapes firms' positioning in introduction, growth, maturity, and decline phases. To achieve the objective the study utilizes panel data from publicly listed Indian manufacturing firms covering the period between 2010 and 2022. Intellectual capital efficiency is measured using the Stochastic Non-Parametric Envelopment of Data (StoNED) approach, and its association with life cycle stages is evaluated through multinomial logistic regression. The findings demonstrate that firms in the maturity stage exhibit the highest intellectual capital efficiency, while firms in the introduction and decline stage exhibit significantly lower scores. Findings also show that intellectual capital efficiency influences the likelihood of firms being in an introduction and decline stage. These findings suggest that efficient and strategic utilization of intellectual capital is key to firm progression in emerging markets. Importantly, the current study further reveals that intellectual capital efficiency exhibits procyclical aligned with macroeconomic business cycle phases, with efficiency peaking during economic expansion and declining during contractionary periods underscoring sensitivity of intangible resource utilization to aggregate demand conditions. This study

contributes to intellectual capital and firm strategy literature by integrating StoNED based efficiency benchmarking approach with life cycle theory and business cycle analysis in the context of emerging markets. Policymakers may also draw on these insights to design targeted initiatives that enhance manufacturing productivity, foster innovation, and strengthen the resilience of firms across different life cycle stages, thereby supporting progress towards the achievement of the Sustainable Development Goals. Such measures can support more productive, adaptive, and sustainable industrial development in emerging markets.

Key Words: Intellectual capital efficiency; life cycle theory; stochastic non-parametric envelopment of data; resource-based view; multinomial logistic regression, business cycle; emerging economy

JEL Classification: O34, E32

1. Introduction

Intellectual capital (IC) at firm level refers to unified set of unique intangible assets comprising human, structural, relational and innovation elements that are considered as critical factors of organizational performance in a time when competitive and sustained success depends mostly on innovation, knowledge and creativity [44], [31], [54], [70]. The existing literature consistently underscores the transformative role of IC in enhancing operational efficiency and overall productivity within a business unit [60], [25], [34], [44]. Additionally, investing in IC is increasingly recognized as a core contributor for sustained strategic advantage [6], [61], [43].

A critical yet underexplored dimension in existing IC research concerns the relationship between IC efficiency and macroeconomic business cycle fluctuation. Business cycle is characterized by alternating phases of expansion and contraction in aggregate economic activity which profoundly shape firm's operating environment, investment capacities and resource utilization pattern [89], [16]. During expansionary phase favorable credit conditions, rising demand and improved investor sentiment tend to encourage investment in intangible assets including human capital development, research and development and organizational systems. On the other hand, when economy contracts first tend to reduce discretionary expenditure on knowledge intensive, which lead to reductions in the efficiency of IC. Despite this intuitive connection, empirical research has mostly ignored the role of macroeconomic cyclicality in this process and how it affects the IC efficiency in different stages of the firm's life cycle. This neglect is even more significant in less developed economies such as India, where the business cycle intersects with structural institutional characteristics to yield unique cycles of intangible assets accumulation and depletion [48], [62].

IC is considered as a strategic resource that creates a competitive advantage on several levels across the globe [6], [61] from the perspective of resource-based view (RBV) theory. In the fast-changing business landscape, firms have to rely on intangible resources to improve productivity, creativity and competitiveness for them, IC has become the root system of the firms to leverage intangibles factors for improving productivity, creativity and competitiveness [6], [43], [54], [60], [61], [71]. Importantly these

strategic relevance of IC are not exclusive to developed economies but have increasingly been a feature of emerging markets where firms are more likely to face instructional voids and resource constraints and to depend more heavily on knowledge based resources to meet these need [60], [71].

India come out as one of the world's largest emerging economies and home to a diverse manufacturing sector but also constrained by limited resources, technological gaps and intense global competition. In this context, the effective management and utilization of IC become particularly important for addressing structural inefficiencies and achieving sustainable growth. Consequently, understanding the way firms transforms IC resources into value (intellectual capital efficiency (ICEF)) of firms in such a scenario not only highlight information on resource efficiency but also enables firms to meet their strategic priorities to be competitive in the dynamic business environment [68].

The relevance of intellectual capital efficiency extends beyond firm-level performance to the broader objective of sustainable industrial development. Manufacturing firms depend on employee knowledge, organizational system, stakeholder relationships and innovation capabilities to utilize resources productively, adapt to changing market conditions and maintain competitiveness over time [94]. Understanding how efficiently these knowledge based resources are utilized across firm cycle stages is relevant to Sustainable Development Goal (SDG) 8, which emphasizes sustained economic growth and productive economic activity and SDG 9 which promotes resilient industrial development and innovation [95]. Moreover, the sensitivity of ICEF to macroeconomic fluctuations

raises a important development concern as firms may find it difficult to maintain investments in knowledge and innovation during periods of economic deceleration. By examining Indian manufacturing firms over time, the current study provides evidence on the organizational and economic conditions associated with ICEF, thereby contributing to a broader understanding of sustainable industrial development in emerging economy.

Despite the growing recognition of the IC worldwide, its measurement poses significant challenges due to its intangible nature [63], [77]. Traditional methods for evaluating ICEF, such as basic financial ratios or linear performance models, often fail to capture the complex, multifaceted characteristics of IC [9], [22]. These limitations have induced the need to adopt more sophisticated efficiency estimation technique that can better reflect the stochastic and non linear properties of intangible assets. Therefore, the present study employs the Stochastic Non-parametric Envelopment of Data (StoNED) approach, a hybrid methodology that integrates the strengths of Data Envelopment Analysis (DEA) and Stochastic Frontier Analysis (SFA), to tackle these shortcomings of conventional approaches [9], [66] . StoNED offers a robust framework for measuring efficiency by accounting for random noise and allowing for the flexibility needed to assess diverse components of IC [39]. [81].

However, measuring ICEF at a single point in time provides only a partial understanding of its strategic role. The efficiency and relevance of IC are not static but evolve as firm's progress through different stages of their life cycle. Firms passes through several phases

of life such as introduction, growth, maturity, and decline that affect the way they leverage and gain from the resources which are under the ambit of IC [47], [50], [77]. Firms in the growth stage, for example, might devote more resources towards innovation and human capital development [51], thereby increasing IC efficiency. Conversely, firms in the decline stage might find it difficult to keep efficiency because of resource limitations or antiquated procedures [41]. Therefore, benchmarking ICEF across firm life cycle stages offers critical insights into the way firms can better align IC management strategies with their evolving developmental needs.

Considering the rationale mentioned, the present study proceeds with novel contributions to existing stream of literature in the field of IC. First, it measures the IC efficiency of listed manufacturing firms in India using the StoNED methodology. This approach addresses the complexities and variability associated with intangible assets, offering a robust framework for evaluating IC efficiency [39] in an emerging economy i.e. India.

Finally, the current study contributes to the sustainable development discourse by examining ICEF as a capability relevant to productive industrial development and organizational resilience. By considering firm life cycle stages alongside macroeconomic business cycle conditions, the analysis highlights why the efficient deployment of knowledge based resources may vary across organizational and economic circumstances. This perspective provides a basis for understanding how manufacturing

firms can strengthen adaptive capabilities and sustain innovation oriented development, with particular relevance to SDGs 8 and 9.

Additionally, the current study endeavored to analyze ICEF at distinct life cycle stages of firms to answer research questions such as how does ICEF vary throughout the different stages of firm's life cycle? The purpose of this analysis is to determine if there are patterns or changes in IC effectiveness at the different stages of the firm's life cycle. Furthermore, this work provides an additional perspective to existing literature by delving into the relationship between ICEF and firm's life cycle stages aiming to answer another key research question that is what impact does ICEF have on the likelihood of firms being in different life cycle stages and what role does it play in transitions among these stages over time? This investigation aims to understand how the interaction with ICEF can affect a company's position and strategic (action) at various stages of their life cycle: Introduction, growth, maturity and decline. By examining the interactive relationship between ICEF and life cycle progression the current study highlights the potential of IC as a critical factor shaping firms' developmental trajectories within the evolving economic landscape of an emerging market like India.

The study is organized into four sections: Section2 presents the theoretical and empirical background. Section 3 describes the data, methodology and results, followed by a discussion. Finally, the final section offers conclusions, following implications and future directions regarding the study.

2. Literature Review

2.1 Framework of intellectual capital

&. IC defined as the hidden resources that are not comprehensively recorded in financial records, due to its intangible properties, including workers' knowledge, competencies, experiential insight, working tactics, organizational processes, and customer relationships [44]. These intangible assets are broadly categorized into three core elements that are human capital(HC), structural capital(SC) and relational capital(RC) [22], [31], [54], [70]. These elements form the foundation of a firm's operational capability to innovate, adapt, and sustain its competitive positioning in an increasingly knowledge-driven industrial era. HC, a major component of IC, encompasses employees' knowledge, skills, and competencies both explicit and tacit that drive organizational value [23], [32], [44], [60], [71]. SC refers to internal systems, processes, intellectual property, and organizational culture that support employee performance and operational efficiency [25], [44]. RC captures value from external stakeholders, including customer loyalty, brand equity, and partnerships, crucial for sustaining competitive advantage [42], [57]. In addition, INC has gained prominence for its role in fostering creativity, product development, and R&D investment [34], [80]. Beyond financial support, INC involves structures that promote innovation and adaptability in dynamic markets [57] . Together, these dimensions enable firms to generate value beyond tangible assets, leading to innovation, stronger performance, and greater customer satisfaction.

2.2 Methodological framework for measuring intellectual capital efficiency

Realizing the worth of IC attracts the focus of research and academician to find out a methodological approach that can be employed to measure the complex nature of intellectual resources to evaluate their value driving power. Consequently, various methodologies have been developed including ratio analysis approaches (Skandia Navigator, Tobin's Q, Maret-to Book ratio, Value added intellectual coefficient Method, modified value-added coefficient method), parametric approaches, non-parametric approaches to evaluate intellectual efficiency of firms [17], [20], [58]. Among this ratio analysis approach is one of the most classical and widely used approaches. There widespread adoption is attribute to their transparency, ease of interpretation and applicability across different industries [25], [77].

However, despite the ease of applicability, these methods have been criticized for ignoring the qualitative aspects of IC [22], [56]. To overcome these limitations researchers has increasingly applied parametric and non-parametric methodologies. Parametric approaches, such as SFA, incorporates the statistical modelling and predefined functional form to estimate IC efficiency which may introduce bias if chosen form does not accurately reflect the production process [58]. On the other hand, DEA as a non-parametric approach allows for evaluation of efficiency using a flexible approach that avoids predefined functional form on the data [22], [56]. It constructs an efficient frontier using linear programming based on observed inputs and outputs. Researchers have explored a hybrid methodology known as StoNED that merges the analytical capabilities of both DEA and SFA. Over the year StoNED has been successfully applied in various fields,

including energy efficiency [37], cost efficiency [40], water efficiency [52], soler power efficiency [14], carbon efficiency [66] and so on. To date only Kweh *et al.,* (2022) have applied the StoNED methodology to evaluate IC efficiency of Taiwanese listed firms. This indicates that the full potential of StoNED has yet to be explored in IC related research, particularly in different economic and industrial organization contexts. Therefore, the current study contributes by exploring this methodology in emerging economies like India context.

2.3 IC and RBV theory

The RBV theory outlined by [6] infers that a firm's strategic edge is rooted from its capacity to obtain and effectively manage resources that are unique, scarce and difficult to imitate. According to the RBV theory, these strategic resources are the key to a firm's sustained success, as they enable it to outperform competitors [6], [61], [43]. Traditional resource bases typically include tangible assets like land, plant, machinery, equipment, and financial capital, however, the theory extends beyond physical assets to include intangible assets or resources that are not easy for the competitors to copy and reproduce [43], [72]. These intangible assets, particularly IC, have become increasingly recognized as vital components of firm's resource base in modern knowledge economy. IC comprises HC, SC, RC and INC all of which align with the principles of RBV by fulfilling the valuable, rare, inimitable, and non-substitutable criteria [21], [43]. These dimensions of IC collectively enhance a firm's ability to innovate, adapt, and maintain a competitive advantage.

Furthermore, sustainable industrial development requires firms to maintain productive capability, adapt to technologies and market changes and utilize organizational resources effectively over time. Intellectual capital is relevant to this process because employee knowledge, organizational system, stakeholder relationships and innovation capabilities can support productivity, adaptation and the development of new products and processes [96]. However, the possession of intellectual capital does not necessarily ensure that these resources are utilized efficiently. Examining ICEF therefore provides a useful perspective for understanding how firms convert knowledge based resources into organizational value. The relevance of this efficiency to sustainable development may also depend on organizational maturity and the wider economic environment. Firms at different life cycle stages face different resource requirements, while macroeconomic expansion and contractions may influence their capacity to maintain investment in human capital, organizational systems and innovation [23]. This perspective connects ICEF with SDG 8 through its relevance to productive economic activity and sustained organizational performance, and with SDG 9 through its connection with innovation oriented and resilient industrial development.

2.4 Intellectual capital, RBV theory and firm life cycle theory and Business cycle dynamics

Life cycle theory posits that firms typically undergo four life cycle phases including (i) introduction, (ii) growth, (iii) maturity, and (iv) decline, each marked by particular

opportunities and obstacles. A firm's ability to navigate these stages successfully depends heavily on the resources it can access and leverage.

The RBV theory offers a valuable perspective on how a firm's resources impacts its progression through these stages by highlighting the importance of valuable, scarce, unreplaceable, and non-substitutable resources in sustaining competitive edge. Researchers have argued that the level and nature of internal resources and capabilities are fundamental to shaping organizational development and sustaining competitive advantage over time [18]. [26] through dynamic resource based theory explain how the growth and development of firms depends upon the efficient interplay between their unique resources and their strategic management.

Firms with flexible resource bases like those that have invested in dynamic capabilities, such as innovation and human capital, may find opportunities to shift into new markets or reinvent themselves through restructuring. Firms that have neglected to maintain or enhance their resource base often struggle to reverse the decline, leading to a potential threat to exit from the market. Throughout the firm's life cycle, the nature and structure of resource base evolve to meet the changing demands of each stage [59]. At early stages, the focus is on accumulating and leveraging unique, innovative resources, while at the later stages, the emphasis shifts toward optimizing resources to sustain for long-term. The RBV theory, thus, emphasizes the importance of well managed resources in facilitating the surviving power to thrive at each life cycle stage.

Numerous studies have consistently analyze the significance of firm life cycle stage on various financial decisions including financial structure, decisions on dividend distributions, investment decisions, cash management practices and IC management decisions to make strategic choices for navigating financial challenges [2], [67]. In the existing IC literature, previous research has focused on the way IC affects firms operational performance over various life cycle stages [41], [77]. Like Xu and Liu [77] investigate the repercussions of IC on sustainable performance at different life cycle stages and claimed through their results the key role of HC on financial performance at growth, maturity and decline stages. [51] examine the way IC affects small and medium-sized businesses during several phases of life. The study underlined that whilst the benefits of SC and RC on performance were constant over several life cycle phases, HC had a more noticeable impact during the growth stage. [75] investigated the repercussions of IC and its facets on financial performance over firm's life phases and claimed that HC, SC and INC have proactive impact on financial performance at introduction stage. Furthermore, the study also claims that HC plays a key role in revival stage of firm life cycle.

Despite these insights, there is a dearth of literature which studies the repercussions of IC throughout the phases of firm's evolution. IC, as a strategic component of a firm's resources, contribute to sustainable competitive advantage and long-term success and act as backbone that supports the coordination and enhancement of physical assets and workforce capabilities [86]. Through the accumulation of knowledge and development of

internal system such as documentation procedure, database, and patents firms create an environment where expertise is preserved and leveraged effectively [41], [77]. This formalized knowledge enables firms to keep operating efficiently, react quickly to changes in the market, and keep constant innovation. Therefore, the present study argues that the accumulation of such resources is the determining factor that can uncover the firms' status and development through different life cycle stages [75]. Thus, on the grounds of the above literature background, the current paper proposes the following hypotheses:

H1: Intellectual capital efficiency differs significantly across the different life cycle stages of firms

H2: Intellectual capital efficiency significantly influences the likelihood of firms being positioned in different life cycle stages.

H3: Intellectual capital efficiency exhibits procyclical variation aligned with macroeconomic business cycle phases, with efficiency levels being systematically higher during economic expansion periods than during contraction periods.

The current study frame these hypotheses on the grounds of the RBV theory that asserts how a firm's resources and capabilities, including IC, are pivotal for achieving a competitive advantage [7], [26], [79]. Since firms allocate and utilize resources differently throughout their life cycle stages [10] such as prioritizing innovation during the introduction stage and focusing on structural and relational aspects in the maturity stage. Therefore, it is logical to expect variation in IC efficiency (ICEF). Similarly, the life cycle

perspective highlights that firms must adapt their resource deployment over the course of developmental stages, with IC playing diverse roles at different stages [26]. For example, mature firms typically exhibit the highest ICEF levels due to optimized resource use, while firms in early or declining stages use ICEF to address challenges unique to their circumstances [51], [75].. Prior studies also claim that the firms at maturity stage have already overcome resource intensive hurdles of introduction phase, enabling to utilize them effectively [23], [24]. By integrating RBV and life cycle theory, this study shed new light on existing debate by empirically examining how ICEF varies throughout firm life cycle stages and how ICEF influences the positioning of firms across these stages.

3. Research Methodology

The present study aims to measures ICEF and analyze its distribution across different lifecycle stages and thereafter evaluate the interrelationship between ICEF and firms' life cycle stages. The ICEF is measured through the StoNED approach, and then the efficiency of each firm is evaluated with respect to each stage. To explore the relationship between ICEF and life cycle stages, a multinomial logistic regression is employed on publicly listed manufacturing Indian firms on the Bombay Stock Exchange for the period 2009- 2010 to 2021-2022.The selection of this particular sector is on the basis of the rationale that the Indian manufacturing industry has evolved into a prominent player on the world stage driven by vast economic development, government initiatives like Make in India, and growing its focus toward technological innovation [48], [74]. On the other hand, selection of time frame (2009-10 to 2021-22) is as that this period encompasses

crucial phases of growth and transformation in the manufacturing sector including the impact of global market dynamics, the implementation of policy reforms, and the increasing emphasis on innovation and sustainability [62]. The study uses audited financial data that is accessed from the ProwessIQ database of Centre for Monitoring Indian Economy. The criteria for data selection are: (1) firms must be in continuous operation prior to 2009-10 to support longitudinal analysis and (2) firms must provide complete information of all required indicators for the given period for analyzing the ICEF framework and associated relationship testing. The final data set comprises 3,991 firm-year observations, representing 307 firms i.e. DMUs for evaluation.

3.1 Stochastic Non-parametric Envelopment of Data (StoNED)

The StoNED model developed by [36] offers a unique contribution by combining the structural flexibility of Data Envelopment Analysis (DEA) with the statistical rigor of Stochastic Frontier Analysis (SFA), enabling a more comprehensive efficiency assessment [4], [66]. It estimates a non-parametric, piecewise linear frontier similar to DEA, while incorporating a stochastic component to account for noise and measurement error [39], [40]. Although earlier models have introduced statistical noise in efficiency analysis [29], [83], [84], StoNED stands out by unifying key features of DEA and SFA into a single hybrid framework.

Previous theoretical and empirical studies suggest that the model StoNED approach relies on two common vectors or matrices (input-output vectors) may be denoted as x_i and y_i(refer equation1) for observed decision making firms denoted as i = 1,2,…n [4], [39],

[82]. To deal with multidimensional inputs and outputs directional distance function (DDF) with given directional vectors $g^x$and g^y, respectively is suggested by previous literature [4], [66] for the production possibility set T.

$$\vec{D}_T(x, y, g^x, g^y) = \sup_{\theta}\{\theta|(x - \theta g^x y + \theta g^y)\widehat{I}\,T\} \quad (1)$$

$$\vec{D}_T(x_i^*, y_i^*, g^x, g^y) = 0, i = 1, \ldots n. \quad (2)$$

Here, the vector (x_i^*, y_i^*) in the direction (g^x, g^y) reflects the reference input-output combination for firm i. Viewed from theoretical standpoint, this outcome constitute the firm's profit maximizing solution in the absence of predefined behavioral assumptions [81]. Furthermore, (x_i^*, y_i^*) is considered to resides on the boundary of the production possibility set T, regardless of the firm's objectives. Consequently, the DDF satisfies Equation 2.

In the direction (g^x, g^y), the measured input–output vectors from the set $\widehat{I}\,R_+^{m+s}$ are subject to the random inefficiencies u_i and noise v_i , which together form the composite error term $\varepsilon_i = u_i + v_i$. This can be represented in Equation (3), where the actual data reflect the variation of the ideal input–output vector due to these disturbances. It is assumed that $u_i\ and\ v_i$ that represents random inefficiency and noise, respectively, have the same variance and are uncorrelated of each other similarly to the assumptions of standard SFA model [4], [19]. Moreover, direction vector (g^x, g^y) denotes the impact of $u_i\ and v_i$ (inefficiency and noise) on specific input and output variables. If (g^x, g^y) is equal to 0 in

the data generation process (DGP), the input or output variables remains unaffected by $u_i \; and \; v_i$. Additionally with the rise in the values of (g^x, g^y) the impact of inefficiency (u_i) and noise (v_i) on the pertinent variable becomes more significant. As per above mentioned DGP, the value of DDF is equal to the composite error term which is expressed in equation 4 form by [92].

$(x_i, y_i) = (x_i^* + \varepsilon_i g^x, y_i^* - \varepsilon_i g^y)$, i =1,…n,. (3)

$\vec{D}_T(x_i, y_i, g^x, g^y) = \varepsilon_i \quad ''i.$ (4)

This approach follows the following stage procedure, where first step involves estimating the conditional mean distance [4], [81], as defined by Equation 5.

$d_T(x_i, y_i, g^x, g^y) = \vec{D}_T(x_i, y_i, g^x, g^y) - \mu$ (5)

$$MIN \sum_{i=1}^{n} (x_i y_i g^x g^y)$$

Subject to. (6)

$$d\hat{I}\Delta$$

The array Δ in equation 6 comprises directional functions that satisfy the essential criteria unconstrained disposability, convexity, and translation invariance, thereby reinforcing the validity of non-parametric model. The convex non-parametric least square(CNLS) estimator is used to the DDF framework in order to solve the infinite-dimensional least

squares issue stated in equation 6. Brute-force numerical approaches cannot, however, solve equation 6 since it entails a sophisticated, unbounded-dimensional programming. The main challenge lies in finding a parametric method that satisfies the necessary conditions for numerous functions. To handle this , ([35]; [92], introduced a finite dimensional quadratics programming model with equivalent properties as described by equation 6. The residual error term $\widehat{\varepsilon}_i^{CNLS}$ represents the estimated value of $\vec{D}_T(\mathrm{x_i}, \mathrm{y_i}, g^x, g^y) - \mu$. [92] introduced a new firm-specific coefficient, γ_i , to capture the marginal effects of outputs on the DDF.

$$\underset{\alpha,\beta,\gamma,\varepsilon}{MIN} \sum_{i=1}^{n} = \left(\varepsilon_i^{CNLS}\right)^2$$

Subject to.

$\gamma_i y_i = \alpha_i + \beta_i' x_i - \varepsilon_i^{CNLS}$, " i =1,…,n,

$\alpha_i + \beta_i' x_i - \gamma_i' y_i \mathfrak{f} \alpha_h + \beta_h' x_h \gamma_h' y_h$, " h, i =1,…,n,

$\gamma_i' g^y + \beta_i' g^x = 1$, " i =1,…,n, (7)

$\beta_i^3 0$ " i =1,…,n,

$\gamma_i^3 0$ " i =1,…,n.

The first set of constraints models the distance to the frontier as a linear function of inputs and outputs. The inequality constraint in Equation 7, interpreted as a system of Afriat

inequalities, ensures global concavity [40], [85]. The second set imposes monotonicity on inputs and outputs, ensuring free disposability, convexity, and translation invariance [35]. The third constraint normalizes the function of guaranteeing translation quality [66]. After solving CNLS problem, the deterministic frontier is estimated via corrected CNLS, or the stochastic frontier via the StoNED approach. Adjusting the CNLS estimate of distance (d) is essential for deriving the directional distance function by incorporating inefficiency in the chosen direction (g^x, g^y). The final output of the directional distance function based StoNED model is the efficiency score, bounded between 0 and 1.

3.2 Variable description

3.2.1 Dependent variable

Firms' life cycle stages is dependent variable in current analysis which is classified using [15] five stage framework including(i) introduction, (ii) growth, (iii) maturity, (iv) shakeout, and (v) decline. These stages, drawn from research on market share, production, learning and entry/exit pattern, reflect distinct financial and operational traits [15], [65]. Classification is based on cash flows from operating, investing and financial activities. **Table 1** describes the criteria used to classify each life cycle stage of firms.

Table 1 Life cycle stages measurement description

Stage	Cash Flow from Operation	Cash Flow from Investing	Cash Flow from Financing

Introduction	<0	<0	>0
Growth	>0	<0	>0
Maturity	>0	<0	<0
Decline	<0	>0	≤ or ≥ 0
Shakeout	Rest of the firms are classified under this category		

3.2.2 Independent variables

ICEF, serving as the independent variable, is measured using the StoNED approach with four inputs and two outputs, based on prior studies [25], [42], [57]. To derive efficiency scores through StoNED dimensions of IC are proxied as input variables, which are HC, SC, RC, and INC. HC is proxied by total employee compensation [41]. SC is measured through administrative expenses, including rent, repairs, and depreciation [7]. RC is represented by selling and marketing costs and INC by R&D expenditure [7], [51], [77]. On the other hand, market capitalization (MC) and net revenue (net sales) (NS) are used as proxies of the output variables [38], [79]..

3.2.3 Control variables

The present investigation also includes firm-specific control variables that may influence a firm's life cycle stages. Firm size (log of total assets) denoted as Size, reflects resource availability and resilience [69]. Leverage (debt-to-equity ratio) denoted as Lev, captures financial risk and strategic expansion, with high debt often linked to later-stage distress [63]. Sales growth (ΔSG), calculated as the difference between current and previous

year's sales, indicates performance shifts across life cycle stages [23]. Firm age (NLAGE), measured by the natural log of incorporation year, accounts for organizational experience [13], [24]. Tangibility (ratio of net fixed to total assets) reflects strategic flexibility and capital structure [69]. Return on equity (RoE), calculated as net income over shareholders' equity, captures profitability across stages [23]. Lastly, the current ratio (CR), representing liquidity (current assets over liabilities), is included to assess short-term financial health [3].

3.2.4 Multinomial logistic regression

Since the dependent variable in this current investigation is life cycle stages which is a categorical variable measured as per the Dickinson [15] measurement criteria taking cash flow information as proxy, takes the forms of 0 for Introduction, 1 for growth, 2 for maturity, 3 for shakeout and finally 4 for decline, the usage of Multinomial Logistic Regression (MNL) is preferred. MNL is appropriate for nominal outcomes with more than two categories [8], [23], [73],, extending binary logistic regression to estimate the probability of each outcome based on one or more independent variables [12]. The model estimates the likelihood of a firm being in a particular stage relative to a reference category. In this study, the dataset includes 347 listed firms observed from 2009-10 to 2021-22. Let Y_{it} represents the life cycle stage for firm i at time t, were

where = 1 , … , 347 and t varies by firm. Vector X_{it} includes ICEF and relevant control variables.

$$\log\left(\frac{\pi_{itr}}{\pi_{it1}}\right) = \alpha_r + X'_{it}\beta_r + u_{ir}, \quad r = 1\ldots\ldots, R \qquad (8)$$

where, $\pi_{itr} = Pr\ (Y_{it} = r)$ is the probability of the i^{th} firm being in the r^{th} life cycle stage at time t, α_r represents the intercept, β_r is array of parameters for the independent variables, and u_{ir} is an error term. The main independent variable of interest is ICEF, while control variables include SIZE, LEV, RoE, Δ SALES, and NLAGE, among others.

The likelihood function for firm i is:

$$l\ (\alpha_r, \beta_r, \text{and } \sum) = \left\{ \Pi_t^{T_i} \left[\frac{exp(a_r + x'_{it}\beta_r U_{ir})}{\sum_q^R exp(a_q + x'_{it}\beta_q U_{iq})} \right]^{1^{(Y_i r = r)}} \right\} \int_u (U_i, \Sigma)\, du_i \qquad (9)$$

where $l(\cdot)$ is an indicator function, and $fu\ (ui, \Sigma)$ f u (u i ,Σ) represents the multivariate normal density. Due to its complexity, maximum likelihood estimation is performed numerically. A normalization constraint is applied by setting $_3 = 0$, $\beta_3 = 0$ and $U_{i3} = 0$, making the third stage as (e.g., maturity stage) the reference category.

4. Results and Discussion

4.1 Step-1 Analysis-Measuring the ICEF and analysing trends of ICEF across firms' life cycle stage

4.1.1Descriptive statistics and correlation matrix of input-output variables

As per the findings of descriptive statistics (refer **Table 2**) HC is ₹3235.928 million, SC is ₹12171.42 million, RC is ₹2899.548 million, and INC is ₹433.6961 million on average.

Furthermore, the results of correlation matrix demonstrate that the measures of inputs and outputs variables are positive and significant values, supporting their suitability for inclusion in the StoNED framework.

Table 2 Descriptive statistics of input-output variables

Summary Statistics			Correlation Matrix					
	Mean	SD	HC	SC	RC	INC	NS	MC
HC	3235.928	6859.153	1	-	-	-	-	-
SC	12171.42	44593.82	0.744*	1	-	-	-	-
RC	2899.548	8780.229	0.629*	0.605*	1	-	-	-
INC	433.6961	1619.059	0.450*	0.289*	0.278*	1	-	-
NS	65242.12	272600.8	0.696*	0.761*	0.771*	0.266*	1	-
MC	131034.4	515667.8	0.607*	0.717*	0.551*	0.397*	0.617*	1

Note- * Represent Statistical Significance Level at 1% Level of Significance

Authors Own Computation

4.1.2 Analysis of ICEF scores through StoNED approach

Firm wise average ICEF scores varies between 0.216 and 1 (**refer Figure 1**) and standard deviation values varies between 0 to 0.314of ICEF scores measured with the StoNED approach. From 2009-10 to 2017-18, the mean ICEF scores generally improved, raised from 0.563 in 2009-10 to a peak of 0.630 in 2017-18, indicating that, on average, firms became more efficient in utilizing IC (**refer Figure 2**). However, after 2017-18, the

mean values fluctuated slightly, ranging from 0.542 to 0.615, showing a stabilization or slight decline in overall efficiency. Regarding variability, the standard deviation decreased from 0.231 in 2009-10 to 0.213 in 2017-18, reflecting a reduction in the differences between firms in their efficiency levels, suggesting that firms became more consistent in their IC utilization. After 2017-18, the standard deviation slightly increased, reaching 0.234 in 2021-22, indicating that while the average efficiency remained stable, and there was a growing disparity in ICEF across firms.

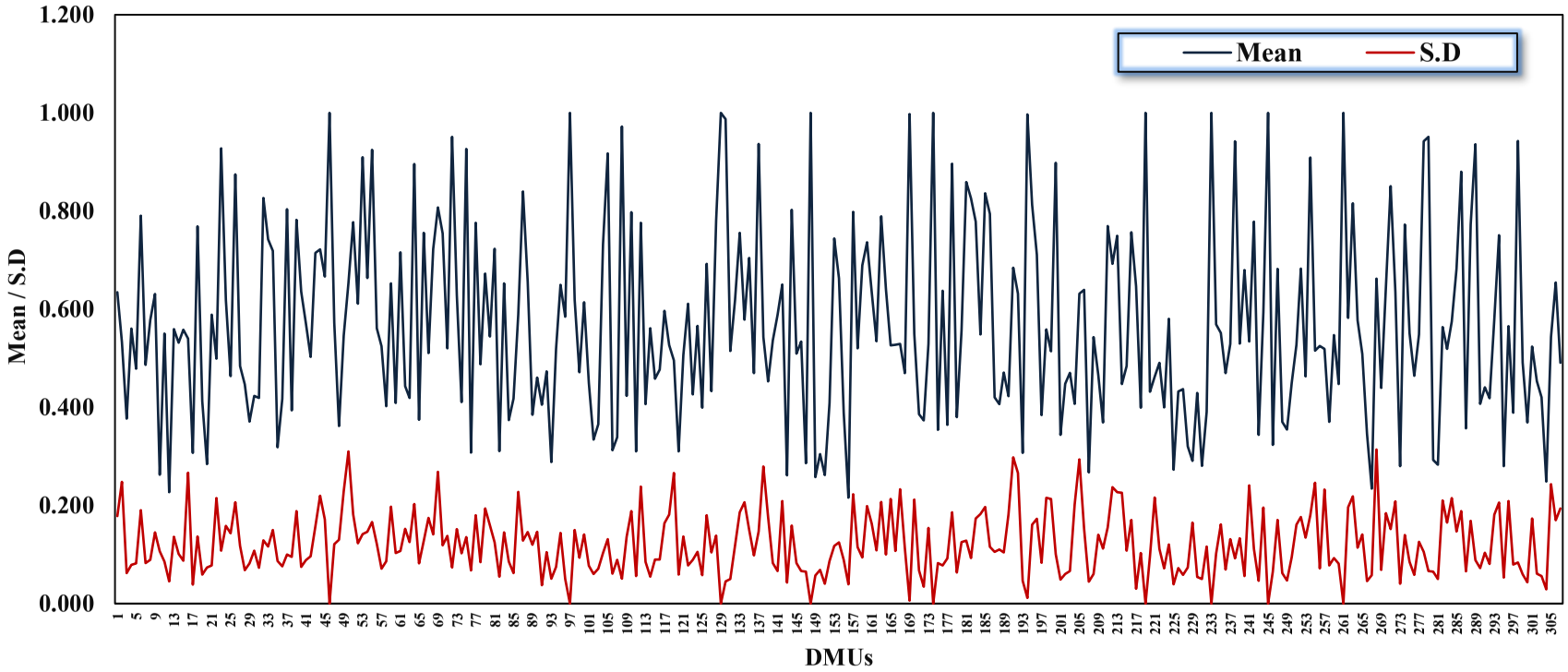


Figure 1 Temporal trend analysis of firm wise ICE
Note- Authors' Own Creation

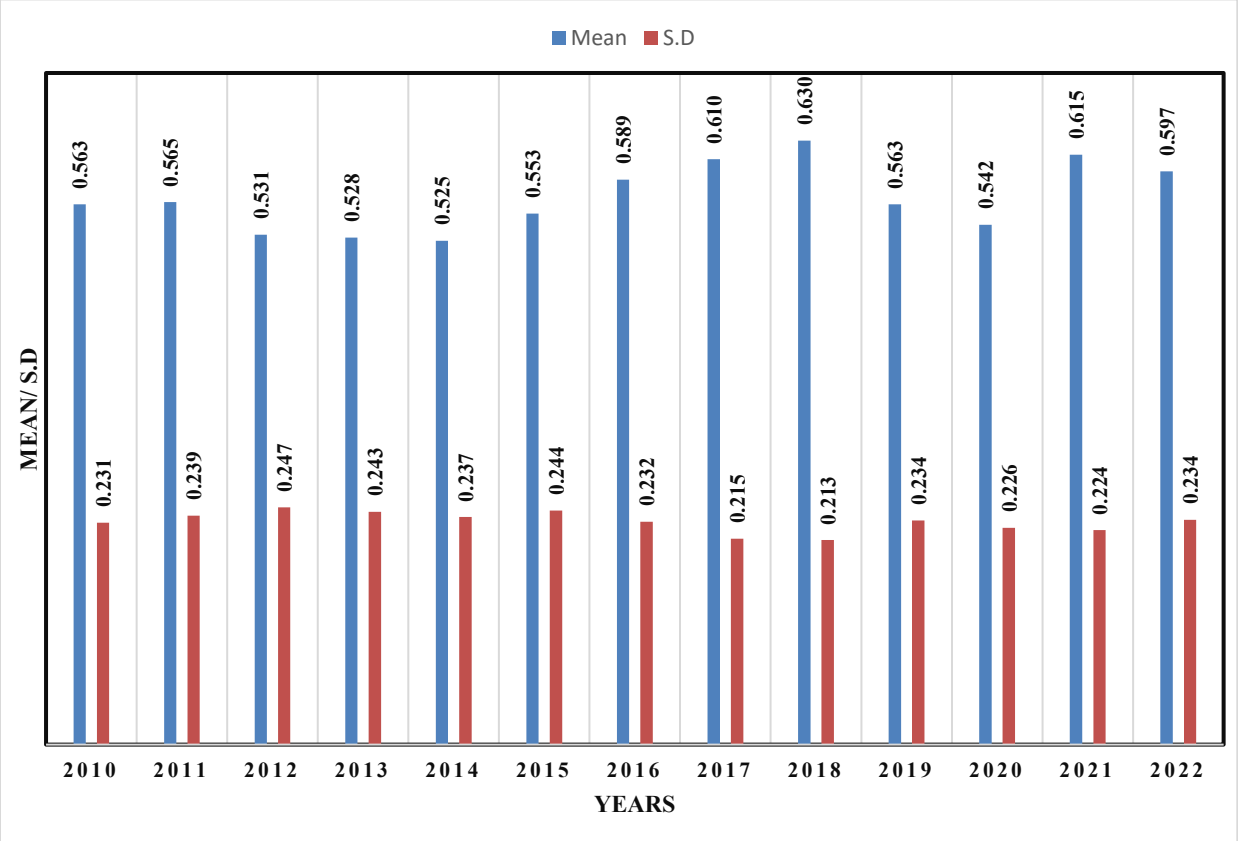


Figure 2 Yearly average and deviations of ICE of firms
Note- Authors' Own Creation

4.1.3 Comparative analysis of ICEF and life cycle stage through a trend analysis and density distribution

The results (refer Table 3) show that the maturity stage consistently accounts for the highest number of efficient firms, with 2498 out of 3991, indicating that mature firms are more adept at leveraging IC due to their established structures. The growth stage records

780 efficient firms, reflecting progress but also challenges in scaling IC. The introduction stage has 184 efficient firms, highlighting early-stage limitations like high investment needs and learning curves. The decline stage (106 firms) reflects difficulty in sustaining IC efficiency amid financial pressures. These patterns suggest that mature firms can serve as IC efficiency benchmark, while growth-stage firms may require strategic IC investments.

The density graph (refer Figure 3) depicts the distribution of ICEF scores across firm life cycle stages. Maturity-stage firms show a concentrated spread from 0.300 to 0.900, often reaching 1.000, indicating consistent and high IC efficiency. Growth-stage firms display a wider range (0.200-1.000), suggesting mixed performance in managing IC. Introduction-stage firms have a narrower range (0.400-0.900), reflecting moderation to high efficiency due to early investments in innovations. Decline-stage firms show scattered and generally lower scores (0.200-0.900), highlighting challenges in sustaining efficiency. These patterns align with temporal trends, reinforcing that IC efficiency varies significantly across life cycle stages.

Table 3 Trends of ICEF in each life cycle stage

Year	Introduction	Growth	Maturity	Shakeout	Decline	Total
2010	18	68	189	26	6	307
2011	29	92	155	28	3	307
2012	13	88	174	23	9	307

2013	22	74	177	25	9	307
2014	17	56	191	33	10	307
2015	12	38	213	33	11	307
2016	10	45	214	34	4	307
2017	3	60	200	35	9	307
2018	6	51	204	36	10	307
2019	11	55	191	37	13	307
2020	10	50	203	42	2	307
2021	11	48	205	35	8	307
2022	22	55	173	45	12	307
Total	184	780	2489	432	106	3991

Note - Authors' Own Computation

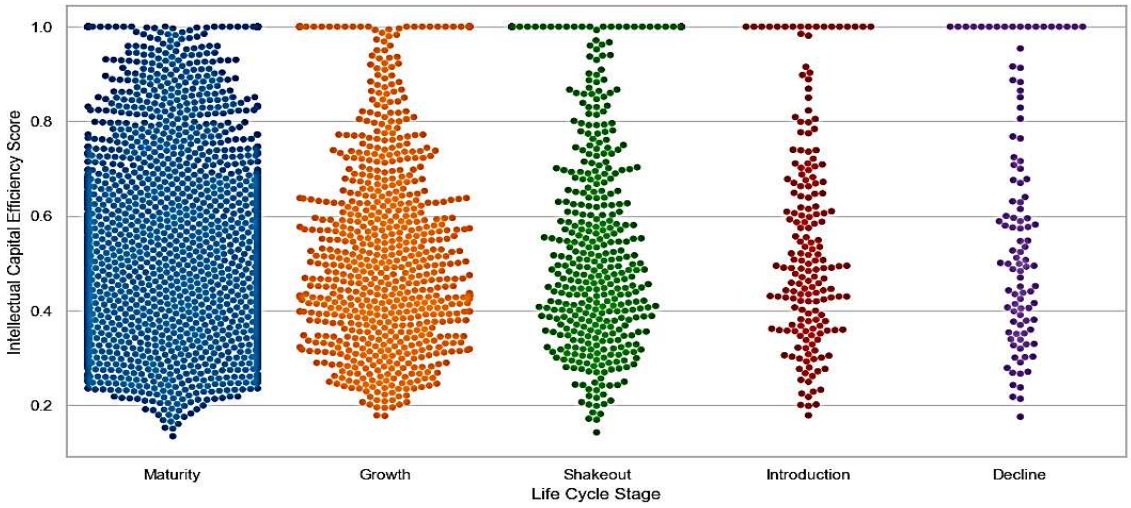


Figure 3 Density visualization of ICE scores by firm life cycle

Note- Authors' Own Creation

4.1.4 Mean difference of ICEF by each life cycle stage

The pairwise comparison of ICEF for different stages evaluated through Kruskal-Wallis test with Dunn's post hoc test (refer **Table 4**) is employed to exhibit that the distribution of characteristics is same in the k-sub population (Gabor, López-Malest & Panait, 2023). The findings reveal significant differences in ICEF across firm life cycle stages. The test statistics of 96.104 is significant at the 1 % level, indicating heterogeneous ICEF distribution among the stages. Dun's post hoc results shows that the growth and maturity stages units exhibit significantly higher ICEF than those in the introduction and decline stages. The decline stage shows the lowest ICEF, likely due to diminishing capacity to leverage intangible assets.

Table 4 ICEF distribution across different life cycle stages

LFS	Obs	Rank Sum	Introduction	Growth	Maturity	Shakeout	Decline
Introduction	184	405,383.00	-	-	-	-	-
Growth	780	1.380	4.562*	-	-	-	-
Maturity	2,489	4.900	2.673*	-4.135*	-	-	-
Shakeout	432	1.030	-1.398***	-5.259*	-3.778*	-	-
Decline	106	254342.500	-1.675**	-8.693*	-6.748*	0.212	-
Chi2(4)	96.104*						

Note (s): *, **, *** represents statistical level of significance at 1%, 5% and 10%.

Authors' Own Computation

4.2 Step-2 Analysis- Analyzing relationship between ICEF and life cycle stage

Descriptive statistics (Table 5) reveal that the mean ICEF values across life cycle stages as in Introduction (0.607), Growth (0.527), Maturity (0.564), Shakeout (0.645), and Decline (0.662). Sales growth (ΔSG) is highest in the introduction stage (27.896), consistent with early-stage expansion, but drops to 9.628 in maturity. RoE peaks during maturity (8.142), though it shows high variability. Tangibility declines from growth (0.343) to decline (0.221), suggesting a shift toward intangible assets over time. Diagnostic checks (Tables 5 & 6) show all variance inflation factor (VIF) values below 5 and no strong correlations, confirming the absence of multicollinearity and supporting valid regression interpretations.

Table 5 Descriptive statistics of regression variables

Descriptive Stats		ICEF	Lev	Size	ΔSG	RoE	NLAGE	Tang	CR
Introduction	$\bar{x}$	0.607	0.047	8.843	27.896	1.839	3.510	0.282	1.415
	M	0.563	0.022	8.823	15.817	1.123	3.526	0.276	1.255
	σ	0.229	0.078	1.616	186.699	5.294	0.477	0.124	1.190
Growth	$\bar{x}$	0.527	0.038	9.509	13.807	5.362	3.578	0.343	1.347
	M	0.472	0.019	9.312	11.715	2.547	3.555	0.337	1.175
	σ	0.226	0.078	1.926	21.499	12.066	0.469	0.135	0.749
Maturity	$\bar{x}$	0.564	0.034	9.531	9.628	8.142	3.714	0.312	1.763
	M	0.514	0.018	9.423	8.497	3.664	3.738	0.299	1.400

	σ	0.232	0.065	1.763	19.677	24.165	0.507	0.152	1.468
Decline	$\bar{x}$	0.662	0.039	9.561	13.078	7.286	3.641	0.221	2.031
	M	0.643	0.018	9.833	6.713	1.976	3.701	0.193	1.465
	σ	0.255	0.069	1.966	39.586	19.447	0.496	0.1305	1.762
Shakeout	$\bar{x}$	0.645	0.033	9.797	9.203	7.038	3.780	0.227	1.962
	M	0.614	0.019	9.771	7.240	3.435	3.784	0.200	1.620
	σ	0.237	0.047	1.724	26.574	11.984	0.449	0.145	1.284
Pooled Data	$\bar{x}$	0.570	0.036	9.525	11.333	7.166	3.683	0.305	1.694
	M	0.519	0.018	9.422	9.218	3.208	3.664	0.296	1.350
	σ	0.234	0.067	1.798	45.433	20.539	0.497	0.150	1.349

Note(s)- "$\bar{x}$" *represents mean, "M" represents median and "*σ" represents standard deviation.

Authors' Own Computation

Table 6 Correlation matrix and VIF analysis

Stats	ICEF	Lev	Size	ΔSG	RoE	NLAGE	Tang	CR	VIF	1/VIF
ICEF	1	-	-	-	-	-	-	-	1.43	0.701
Lev	0.029***	1	-	-	-	-	-	-	1.24	0.804
Size	0.243*	-0.406*	1	-	-	-	-	-	1.18	0.846
ΔSG	0.020	0.074*	-0.019	1	-	-	-	-	1.17	0.858
RoE	-0.001	-0.132*	0.222*	0.020	1	-	-	-	1.16	0.861
NLAGE	0.001	-0.136*	0.207*	-0.049*	0.100*	1	-	-	1.07	0.933
Tang	-0.225*	0.053*	-0.025	0.012	-0.075*	-0.097*	1	-	1.07	0.934
CR	0.097*	0.080*	-0.122*	0.112*	0.040	0.060*	-0.312*	1	1.02	0.977

Note (s): *, **, *** represents statistical level of significance at 1%, 5% and 10%.

Authors' Own Computation

4.2.1 ICEF and firms' life cycle stages

The findings demonstrate that ICEF significantly increases the likelihood of a firm being at the introduction stage as compared to maturity (0.878) (refer **Table 7**). On contrary, ICEF negatively influences during the growth stage as compared to maturity (-0.696), suggesting that firms with higher ICEF are less likely to remain in the growth stage and may transition more rapidly. Furthermore, the findings shows that ICEF positively and significantly impacts the shakeout stage (0.832), while increasing the likelihood of being in the decline stage (1.159), highlighting its role in managing the downturn phase.

Additionally, marginal effects were estimated to provide valuable insights into how predictor variables influence the likelihood of a firm being at different life cycle stages, compared to the maturity stage. A one unit increase in ICEF raises the propensity of occupying the introduction stage by 3.7 percent and decreases the propensity of a firm occupying the growth phase by 13.2 percent, indicating that higher ICEF is associated with firms advancing beyond the initial growth period.

The current study further explore whether firms with higher ICEF levels diminishes the likelihood of entering the introduction, shakeout or decline stages over the next five years, using logistic regression. This analysis builds on prior findings suggesting that about three-fifth of firms in the introduction stage transition to growth or maturity within five year

[23]. Contrary to their claim, the results reveal a consistently robust and significant effect of ICEF across all time points, with coefficients ranging from 2.478 to 3.270 (refer **Table 8**).

Table 7 Multinomial logistic regression results

Dep Variable	Introduction	Growth	Shakeout	Decline
ICEF	0.878**	-0.696*	0.832*	1.159*
	(0.348)	(0.200)	(0.238)	(0.441)
Lev	-1.506	1.176***	0.292	0.715
	(1.479)	(0.648)	(0.973)	(1.597)
Size	-0.192*	0.053***	0.060***	-0.0007
	(0.057)	(0.028)	(0.035)	(0.067)
ΔSG	0.010*	0.008	0.0003	0.006***
	(0.002)	(0.001)	(0.002)	(0.003)
RoE	-0.094*	-0.009**	-0.012**	-0.006
	(0.016)	(0.004)	(0.005)	(0.009)
NLAGE	-0.535*	-0.446*	0.153	-0.368***
	(0.162)	(0.085)	(0.115)	(0.200)
Tang	-3.342*	0.053	-4.066*	-4.615*
	(0.612)	(0.306)	(0.428)	(0.838)

CR	-0.565* (0.122)	-0.410* (0.061)	-0.016 (0.035)	-0.013 (0.061)
Cons	2,721* (0.824)	0.860** (0.411)	-2.212* (0.549)	-1.310 (1.002)
Pseudo R2	0.063			
Observations	3991	3991	3991	3991
Marginal effects ICEF		**Delta Method**		
ICEF	dy/dx	standard error	Z	P>Z
Introduction	0.037	0.014	2.64	0.008
Growth	-0.132	0.029	-4.55	0.000
Maturity	-0.133	0.034	-0.38	0.701
Shakeout	0.079	0.021	3.73	0.000
Decline	0.028	0.011	2.49	0.013
Note (s): *, **, *** represents statistical level of significance at 1%, 5% and 10%. dy/dx = marginal effects, x = ICEF and y = Life cycle stages Authors' Own Computation				

Table 8 Temporal transition of firms' life cycle stages and ICEF

Dependent Variable =	Introduction or shakeout or Decline T+1	Introduction or shakeout or Decline T+2	Introduction or shakeout or Decline T+3	Introduction or shakeout or Decline T+4	Introduction or shakeout or Decline T+5
ICEF	3.270* (0.633)	2.478* (0.498)	2.933* (0.606)	2.736* (0.587)	2.845* (0.642)
Control Variable	Included	Included	Included	Included	Included
Cons	0.691 (0.303)	1.040 (0.474)	1.342 (0.626)	1.441 (0.700)	1.388 (0.715)
Pseudo R^2	0.056	0.051	0.051	0.042	0.038
Note (s): *, **, *** represents statistical level of significance at 1%, 5% and 10%. Authors' Own Computation					

4.3 Discussion

The current study benchmarks ICEF across different firm life cycle stages using StoNED approach. The discussion is organized around three primary hypotheses: (1) ICEF varies across firm's life cycle stages, and (2) ICEF significantly influences the likelihood of firm being in particular life cycle stage and (3) ICEF exhibits procyclical variation aligned with macroeconomic business cycle phases.

The observed significant variation in ICEF across life cycle stage supports H1. As per findings, maturity stage firms show the highest and most consistent ICEF scores, highlighting their ability to effectively leverage intangible assets through established structures and routines. The findings put forward that firms at this stage benefit from a well-established and stable resource base. These findings is in line [49] and [75], who have argued that mature firms tend to perform better than younger ones by taking advantage from their accumulated and refined knowledge, which benefits in enhancing overall firms efficiency.

In contrast, firms in the introduction and decline-stage exhibit more variability and generally lower ICEF, reflecting early stage developmental constraints and late stage operational inefficiencies, consistent with life cycle theory which explains how resource needs and capabilities evolve as firms progress through different stages. This variation in ICEF across different life cycle stages observed through findings align with RBV, which assumes that level and quality of internal resources and capabilities significantly influence the firms growth and its position within the life cycle [18].

The analysis further supports H2 by demonstrating that ICEF significantly influences a firm's life cycle positioning. Findings reveal that higher ICEF increases the likelihood of being in the introduction stage, emphasizing the foundational role of IC in early development. This aligns with RBV's assertion that intangible resources are critical for establishing initial competitive footing.

A notably higher ICEF elevate the probability of firms entering the introduction stage. These findings support the arguments that underscore the critical role of non-physical resources such as human capital, organization process, systems and innovation in the early stage, helps foster a sustainable competitive edge and seizing growth opportunities and deterring market entry from competitors [23], [50]. However, the negative and statistically significant coefficient values of ICEF at the growth stage are that contrary to expectations, higher ICEF may not necessarily contribute to growth during this phase. Instead, firms in this stage may prioritize investment in physical assets to scale up their operations quickly.

Additionally, findings reveal that ICEF significantly increases the probability of firms being at decline stage, emphasizing its relevance even during downturn rely on their intellectual resources to manage challenges. These findings are in support with the argument that the firms in decline stage are more inclined to invest in intellectual resources to rejuvenate firms' capabilities, such as organizations' employees' skills, organization process, systems, know how etc. [91].

Beyond the life cycle dimensions, the findings also provide empirical support for H3, revealing that aggregate ICEF levels among Indian manufacturing firm exhibit a discernible procyclical pattern over the study period (2009-10 to 2021-22). Specifically, mean ICEF scores increased gradually from 0.563 in 2009-10 to 0.630 in 2017-18, corresponding to the general period of economic expansion in India, characterized by growth of the GDP, high corporate investment and improved credit conditions. There is

an upward pattern, which corroborates the idea that as economy grows, firms invest more strongly in knowledge based assets, improve employee education, innovate the organization system and invest in their customer all of which boost IC efficiency [87], [88]. On the contrary, the period after 2017-18 witnessed the stabilization of ICEF and a slight fall (0.545 to 0.615) along with India's transition towards the macroeconomic deceleration phase with deceleration in GDP growth, increase in non-performing assets in the banking sector and decline in private investment. This reduction in the mean of the ICEF is consistent with the finding that in slow growth or recession periods, firms will reduce their spending efforts on intangible assets spending what is necessary to sustain the firm's debt-service obligation in exchange for more short-term liquidity [89].

The increasing divergence in ICEF since 2017-18 (standard deviation rising to 0.234 in 2021-22) also suggests that the cyclical downturn was experienced uneven, with financially strong firms continuing their IC investment and financially weak firms retrenching, as is well documented in the literature on the business cycle [90]. These findings confirms that firms level IC efficiency is not solely a function of internal organizational factors but is also sensitive to aggregate macroeconomic conditions making ICEF a meaningful indicator of business cycle dynamics in emerging economies.

5. Conclusion and Implications

The current study provides insights into how ICEF varies across firm life cycle stages and influences a firm's position within them. It highlights ICEF as a dynamic factor in organizational development, with maturity-stage firms showing consistently higher

efficiency due to optimized structures and resources. The findings underscore ICEF's role as both a performance driver and strategic enabler, shaping firm progression from early stages to decline. Crucially, the present study also establish that IC efficiency in Indian manufacturing firms is procyclical in nature, rising during phases of macroeconomic expansion and contracting during slowdowns. These findings directly links micro-level intellectual capital dynamics to macro-level business cycle fluctuations positioning ICEF as a novel and informative indicator for understandings how aggregate economic conditions shape organizational knowledge utilization. By documenting the co-movement of ICEF business cycle phases, the present study contributes a new empirical perspective toward understanding the cyclical behavior of economic phenomena.

From a sustainable development, the current study highlights ICEF as a relevant consideration in understanding productive and resilient industrial development. The differences observed across firm life cycle stages and with both organizational characteristics and broader economic conditions. These findings offer a basis for considering the way manufacturing firms can maintain their human, structural, relational and innovation capabilities over time. The study is therefore relevant to SDGs 8 and 9, particularly in relation to productive economic activity, industrial resilience and innovation-oriented development. Although the analysis does not directly assess environmental or social sustainability outcome, it extends the discussion of sustainable development by examining an organizational capability that may contribute to the continuity and adaptability of industrial activity.

5.1 Theoretical Implications

Theoretically, this study offers understanding of intellectual capital by integrating insights both from RBV and life cycle theory. RBV assumes that firms gain and sustain competitive advantage through the acquisition and effective deployment of valuable, inimitable and indispensable resources. Furthermore, the findings of study suggest that IC act as a significant contributor in augmenting organizational adaptability and strategic progression across life cycle stages, which is in parallel to life cycle theory which states that firms undergo a sequence of distinct evolutionary stages, and each stage is characterized by unique resource requirement. The analysis of the current study reveals that ICEF not only varies significantly across these stages but also act as a driver facilitating transition particularly supporting progression from growth to maturity and resilience in decline. Thus, this study theoretically bridges these two frameworks by positioning ICEF as both a strategic resource and a life cycle enabler. Moreover, by demonstrating the procyclical sensitivity of ICEF to macroeconomic business cycle conditions, the current study extends both IC theory and business cycle theory into unexplored territory. It introduces the concept of cyclically-contingent IC efficiency" reflecting the idea that effectiveness with which firms convert intangible resources into value is not solely an internal firm capability but is also modulated by the macro-economic environment. This bridges the micro foundational literature on intangible assets with the macro level business cycle literature, providing a theoretical link between organizational knowledge utilization and aggregate economic fluctuations.

The findings also extend the sustainability relevance of the resource-based view and life cycle theory by highlighting the role of knowledge-based resources in sustaining organizational capabilities under changing economic conditions. The resource based view explains the strategic importance of intellectual capital, while life cycle theory emphasizes that resource requirement evolves as a firm develop. The observed association between ICEF and business life cycle conditions further suggests that the utilization of these resources should be understood in relation to the broader economic environment. Together, these perspectives offer a framework for interpreting intellectual capital efficiency as a capability relevant to long term organizational adaptation and sustainable industrial development.

5.2 Managerial Implications

Managerially, the results offer important implications for firms at different stages. Introduction stage firms should prioritize building IC capabilities early to overcome resource constraints and foster innovation. Growth stage firms must formalize and scale IC systems to sustain momentum and avoid stagnation. Mature firms can leverage their established IC base for optimization and long term value creation, serving as role models for best practices. Firms in decline or shakeout stage should view intellectual capital efficiency as a strategic lever for restructuring and renewal, investing in knowledge assets to regain competitiveness. Here, innovation capital becomes critical in reorienting the

firm's strategic direction, enabling transformation through targeted R&D, technology adoption, and knowledge-driven renewal initiatives.

The findings also suggest that managers should consider the continuity of intellectual capital investment when making resource allocation decisions. Introduction stage firms may benefit from developing employee capabilities and establishing organizational systems, while growth stage firms should focus on scaling knowledge management processes and innovation capabilities. Mature firms can strengthen the continued utilization of established knowledge resources, whereas firm experiencing decline or shakeout may require targeted restructuring, employee skill development and innovation led renewal. In addition, the procyclical pattern of intellectual capital efficiency highlights the importance of maintaining critical knowledge and innovation capabilities during periods of economic deceleration. These measures may support resilience and productive industrial development, consistent with the broader objectives of SDGs 8 and 9.

6. Limitation and Future Scope

While the study offers important insights, there are certain limitations that must be acknowledged. First, the study emphasizes exclusively on publicly listed manufacturing firms in India, which constrains the generalization of the findings to other sectors or economies with differing contexts. Future research could expand the scope of analysis to other sectors, such as technology or services, and explore IC efficiency across diverse economic contexts, including other emerging and developed economies. Second, the

time frame of 2009-10 to 2021-22, while encompassing critical phases of growth and transformation, may not adequately reflect more recent developments, such as the post-pandemic economic landscape. A broader longitudinal or cross-country study could provide comparative insights into the evolution of IC and its interrelationship with firm life cycles. Although the advanced StoNED methodology was employed, it may not fully capture all dimensions of IC due to data constraints and the subjective nature of intangible asset assessments. Refining measurement techniques through the incorporation of advanced methods, such as machine learning models, could improve the accuracy of IC assessments and uncover complex, non-linear relationships.

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