

Indian Journal of Accounting

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Prof. Gabriel Simon Thattil
President
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MESSAGE

Higher education in India is undergoing a shift in terms of reforms and Adoption of the National Curriculum frame- work. NEP 2020 seeks to make education holistic, trans- disciplinary and flexible. A host of innovative academic programmes and courses are being planned in terms of skill-embedded learning and tech-driven learning methodologies. What then emerges is how to stay relevant in terms of Academics and Research. A deeper and insightful understanding of the current learning eco-system and up-skilling and upgrading to meet the emerging needs are crucial considering disruptive technology that has come to stay.

Accounting today has taken a drastic shift from recording, classifying and preparation of financial statements to interpreting and judging results, analysis in a futuristic perspective and enabling full disclosure for stakeholder decision making. Research in finance and Accounting is turning to be all the more relevant in terms of making it inferential and analytical such that it addresses disruptiveness in terms of the emerging technology. This calls for a drastic shift in Accounting Education and research to bridge the gap between professional demand and academic discourse. Indian Accounting Association has been playing a significant role in this transformative approach through developing model curriculum, and promoting collaborative research in Accounting and Finance where the focus is on the merging domains of AI in Accounting, Fin Tech for Finance as well as Forensic accounting. Encouraging young learners through the National Accounting Talents Search Examination NATS and Young Researchers Award are part of these initiatives.

I would appeal to all researchers learners, professionals as well as practitioners to be part of our endeavours in promoting and professionalizing Accounting Education and research in India as we march ahead with the vision of attaining the status of Viksit Bharath 2047.

With an intention to showcase research outcomes in the domains of Accounting, Finance and Financial services, as well as trans-disciplinary research, Indian Accounting Association is bringing out the next issue of IJA. The journal continues to serves as a publication of repute for dissemination of high quality research in Accounting and allied disciplines. I take this opportunity to thank all the contributors of research papers to this issue and sincerely request all my friends to come up with more research work and research publications, which we would gladly welcome. I also thank all our editorial team with special appreciation for the Chief Editor in bring out the current issue. This issue will certainly stimulate interest in further learning and research.

Wishing you all a wonderful research journey, with warm regards.

A handwritten signature in black ink, appearing to read 'G. S. Thattil', with a long horizontal stroke extending to the right.

Prof Gabriel Simon Thattil
President
Indian Journal of Accounting



MESSAGE FROM THE CHIEF EDITOR OF THE INDIAN ACCOUNTING ASSOCIATION

Accounting education is at the verge of sea changes due to technological changes. The use of Artificial intelligence and automation in accounting education has impacted accounting as a whole. Better decisions in business is capable now with the help of data analytics. Many changes can be seen in the accounting curriculum, including forensic accounting, fintech and cyber security. Real life case studies are being extensively used in classrooms to equip students to experience the real life problems. Focus on international accounting standards have given accounting a globalised view. Accounting has partnered with finance, management and other areas to give an interdisciplinary perspective. The need of the hour is to adapt to the changes in accounting and to embrace the changes. The role of academicians, research scholars and students are gaining significance in making the relevant updates. Research scholars can contribute scholarly articles on artificial intelligence in accounting, ESG, fin tech etc. Indian Journal of Accounting provides a platform for research scholars, students, academicians, and policymakers to contribute valuable papers relating to the recent changes in accounting.

Indian Accounting Association has 61 branches across India and around 9000 members. The Indian Accounting Association conducts National Accounting Talent Search Examination every year since 2009 to measure the nationwide accounting knowledge at the junior and senior levels. The best performer in the National Accounting Talent Search Examination is awarded a cash prize of Rs.21000 with a trophy and certificate at the junior level. The cash prize is Rs.25000, trophy and certificate for the senior level. This is usually conducted during February every year. The Indian Accounting Association has recently introduced a model curriculum for the accounting aspirants to provide them with the new insights on the advancements in the accounting field.

I congratulate all the contributors for their commendable articles and look forward to path breaking articles in the field of accounting and finance. I extend my deep sense of gratitude to Prof. Gabriel Simon Thattil for the timely guidance and coordination. My gratitude is due to the Associate Editors, Dr Priya S and Dr Arun Lawrence for their exemplary work. I am indebted to all the panel of reviewers who have done a remarkable job while reviewing the articles and ensured the articles met quality standards.

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Indian Journal of Accounting

GENERAL IMPACT FACTOR 2.4602

Volume 58

No. 01

June 2026

(INDEXED IN COSMOS FOUNDATION &
ELECTRONIC JOURNAL LIBRARY EZB, GERMANY)

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Barriers and Enablers in the Implementation of Kaizen Costing: Evidence from Emerging Markets

Dr. Meghna Chotaliya¹ | Dr. Kavita Laghate² | Mr. Baijul Mehta³

Citation: Chotaliya, M., Laghate, K., & Mehta, B. (2026). Barriers and Enablers in the Implementation of Kaizen Costing: Evidence from Emerging Markets. *Indian Journal of Accounting*, 58(1), 1-11

ABSTRACT

This paper investigates the implementation of Kaizen costing in Indian manufacturing firms, focusing on its strategic role in enhancing cost efficiency. Using a mixed-methods approach, data were collected from 616 respondents across three firms—Raymond Ltd., Windar Renewable Energy, and KiTEC Industries. Factor analysis revealed five key dimensions influencing Kaizen implementation: performance improvement, cost management integration, problem-solving capabilities, organizational outcomes, and implementation barriers. Findings indicate that Kaizen costing significantly improves productivity and cost control, with stronger results in capital goods firms. However, implementation is hindered by employee-level resistance, inadequate training, and weak strategic alignment. The study recommends structured training, continuous feedback mechanisms, and leadership advocacy to sustain Kaizen effectiveness. These insights offer practical guidance for firms seeking to integrate continuous improvement practices into their cost management strategies.

Keywords

Kaizen costing, Cost, Barriers, Productivity

JEL Classification: L6, L7, L11, L60, O14, M2, M20, M21, M11

Introduction

In an increasingly competitive global manufacturing environment, firms are compelled to adopt methodologies that not only drive cost efficiency and improve quality but also promote a culture of continuous improvement. Among such methodologies, Kaizen costing plays a critical role by emphasizing incremental, employee-driven improvements in cost reduction without compromising product quality or customer satisfaction (Yigit, 2022). A company can achieve success in benchmarking through implementing success in kaizen, people mindset, formalization, centralization and integration. (Goni, Tharia, & Suryo, 2018). Unlike traditional cost control systems, Kaizen costing encourages continuous improvements at the operational level through low-cost, common-sense methods that yield significant results over time. Modern cost management practices increasingly link Kaizen costing with broader sustainability goals. When aligned with circular economy principles, it helps firms optimize resource

use and minimize environmental impact, creating both financial and ecological value (Szczerbak, 2023). Naugolnova (2021) reinforces this perspective by emphasizing internal resource optimization and process efficiency as central to contemporary cost management. Further, combining Activity-Based Costing (ABC) with Kaizen enhances cost accuracy and operational decision-making, offering a complementary approach within modern cost frameworks (El-Gibaly, 2024). Kaizen is also associated with qualitative benefits such as improved job satisfaction, better employee morale, and collaborative organizational culture (Barbosa et al., 2012). In India, manufacturing firms—especially those in cost-sensitive and competitive markets—have increasingly integrated Kaizen into their lean management strategies (Gupta & Jain, 2014). However, despite its proven success in advanced economies, the Indian context presents unique challenges. Implementation of Kaizen costing remains inconsistent, hindered by structural rigidities, resistance

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to change, weak feedback systems, and inadequate training (Dhingra et al., 2019; Mittal et al., 2020). Although lean training is often conducted, strategic misalignment and organizational inertia frequently limit the impact of such initiatives. While global studies affirm the positive outcomes of Kaizen costing, empirical evidence from Indian firms remains limited, particularly concerning barriers to implementation and measurable improvements in cost efficiency. Prior literature tends to focus on isolated case studies or conceptual perspectives, lacking robust multi-firm, statistically grounded insights. This study addresses this gap by examining the organizational, cultural, and systemic barriers to Kaizen costing implementation across three Indian manufacturing firms—Raymond Ltd., Windar Renewable Energy, and KiTEC Industries. Using a mixed-methods approach and data from 616 respondents, the study applies factor analysis and inferential statistics to identify key impediments and performance outcomes. Grounded in the Dynamic Capabilities Framework and the Resource-Based View (RBV), the paper positions Kaizen costing as a dynamic capability that enhances organizational adaptability and sustained cost competitiveness.

The paper is organized as follows: Section 1 reviews the theoretical foundations and literature; Section 2 describes the research methodology; Section 3 presents the empirical results; Section 4 discusses the findings and practical implications; and Section 5 concludes with policy and managerial recommendations.

Literature Review

Kaizen costing represents a continuous improvement philosophy that targets incremental cost reductions at the production stage without compromising quality or customer value (Imai, 1986). It is often integrated with lean manufacturing and circular economy principles to optimize resource utilization and enhance sustainability (Szczerbak, 2023; El-Gibaly, 2024). When aligned with tools like Activity-Based Costing (ABC) and Target Costing, Kaizen offers a comprehensive framework for controlling and improving operational costs (Pererva et al., 2025; Kolev, 2023).

Global literature affirms the operational and financial benefits of Kaizen. In Nigeria, Kayode et al. (2019) reported reduced production costs and quality improvements across firms regardless of employee education levels. Kelesbayev et al. (2020) showed that systematic elimination of non-value-

added activities using Kaizen led to significant efficiency gains. Similar positive outcomes were observed in administrative functions (Anzani et al., 2021) and in non-manufacturing sectors such as construction (Omotayo et al., 2020).

Kaizen has also evolved with digital integration. Kolev (2023) introduced “Kaizen Costing 4.0,” integrating IoT and AI tools to enhance sustainability. These developments reflect the method’s adaptability across contexts. Despite its advantages, Kaizen adoption in developing countries faces numerous obstacles. Structural rigidities, resistance to change, and limited training infrastructure have been identified as major barriers (Mittal et al., 2020; Biadacz, 2024). Al-Barghuthi et al. (2020) emphasized the need for formal training and strategic alignment in Jordanian firms. In Poland and Sudan, studies have revealed that cultural resistance, lack of feedback mechanisms, and absence of leadership support hinder implementation (Elhadi & Elhadi, 2016; Biadacz, 2024).

In India, adoption of Kaizen has been sporadic and context-specific. Gupta and Jain (2014) highlighted how firms integrate Kaizen within 5S practices to improve workplace efficiency. Dhingra et al. (2019) demonstrated its value in cost and quality improvement through lean-Kaizen in Indian firms. However, most studies focus on isolated events or case studies (Chittipaka & Sagi, 2012; Kumar, 2015), lacking comprehensive frameworks or multi-firm empirical evidence.

Despite global evidence of Kaizen’s effectiveness, there is limited empirical research in the Indian context assessing its strategic alignment, cross-functional impact, or implementation barriers using quantitative analysis. Moreover, few studies apply theoretical frameworks like the Resource-Based View (RBV) or Dynamic Capabilities to explain firm-level variations in Kaizen effectiveness. This study aims to fill these gaps by analyzing barriers and outcomes of Kaizen costing in Indian manufacturing firms using a validated five-factor model.

The effective implementation of Kaizen practices is deeply influenced by managerial attitudes, perceptions, and commitment. Todorovic, Čupić, and Jovanović (2024) emphasize that managers’ beliefs about Kaizen’s impact on productivity and employee motivation are critical for its success. Foundational works by Imai (1986) and Dora

et al. (2013) further underscore that leadership commitment, strategic alignment, and employee engagement are essential for sustaining continuous improvement initiatives. However, in the context of developing economies such as India, significant institutional and infrastructural barriers hinder widespread adoption. Mittal et al. (2020) identify structural rigidities, limited training infrastructure, and organizational resistance to change as major impediments to Kaizen implementation in Indian manufacturing firms.

A substantial body of empirical literature supports the operational and financial benefits associated with Kaizen Costing. Kareska (2024) presents quantitative evidence demonstrating improvements in key performance indicators such as productivity, cycle times, and defect rates through structured Kaizen practices. In Nigeria, Kayode et al. (2019) find that Kaizen Costing effectively reduces production costs without compromising product quality, irrespective of employees' educational backgrounds. Similarly, Kelesbayev et al. (2020) report efficiency gains and significant waste reduction at the Kentau Transformer Plant through the systematic elimination of non-value-added activities.

The application of Kaizen principles has also extended beyond traditional manufacturing settings. Anzani et al. (2021) document successful implementation of the 5S framework within academic administrative processes, resulting in improved service quality, enhanced workflow standardization, and greater organizational discipline. In Sudan, Elhadi and Elhadi (2016) show that Kaizen practices improve the competitive positioning of industrial firms, findings corroborated by Omotayo et al. (2020), who highlight Kaizen's role in reducing cost overruns in the construction sector when integrated with PDCA cycles and procurement reforms.

In parallel, evolving cost management methodologies increasingly advocate for the integration of strategic and operational control systems. Hematfar, Sanati-arasteh, and Nooryan (2013) argue that Target Costing, while well-established in Japanese firms, remains underutilized globally despite its potential to align cost structures with market dynamics. Building on this, Pererva et al. (2025) propose a dual-framework cost management cycle wherein Target Costing guides the design phase and Kaizen Costing governs the production phase, fostering continuous cost control. Kolev (2023) further

advances the discourse by introducing "Kaizen Costing 4.0," which integrates digital technologies such as the Internet of Things (IoT) and Artificial Intelligence (AI) to enhance sustainability and support circular economy objectives.

Despite these advancements, the adoption of Kaizen and Kaizen Costing in small and medium-sized enterprises (SMEs) and non-traditional sectors remains limited. Biadacz (2024) identifies cultural and structural barriers that restrict Kaizen adoption in Polish SMEs, while Al-Barghuthi et al. (2020) emphasize the need for structured training and systematic implementation in Jordanian firms. Michalski (2020) illustrates modest early gains in a fast-moving consumer goods (FMCG) context, highlighting the incremental nature of Kaizen implementation. Similarly, studies by Kumar (2015) and Panigrahi (2009) demonstrate that even small-scale, assembly-line operations such as the Visi cooler industry can achieve notable improvements in waste reduction and quality enhancement when Kaizen is integrated with tools like Activity-Based Costing (ABC).

While the extant literature affirms the broad utility and benefits of Kaizen and Kaizen Costing, several critical research gaps persist. Limited adoption in SMEs and non-Japanese markets makes Kaizen remains underutilized in SMEs across developing and emerging economies due to cultural inertia, infrastructural deficiencies, and lack of institutional support. Although conceptual frameworks such as Kaizen Costing 4.0 have been proposed, empirical research exploring the integration of digital technologies (e.g., AI, IoT) into Kaizen practices is scarce. In many organizational contexts, Kaizen is perceived narrowly as a cost-control mechanism rather than as a comprehensive, strategic approach to organizational transformation. While Kaizen principles have been applied in service industries, there is a dearth of comprehensive implementation frameworks and robust performance measurement systems tailored to these settings. The majority of existing studies adopt cross-sectional designs, offering limited insights into the long-term impact and sustainability of integrated approaches involving Kaizen and Target Costing. There is minimal research on context-specific training frameworks and change management strategies that facilitate the successful institutionalization of Kaizen in diverse organizational environments.

Addressing these gaps is essential to advancing

the theoretical and practical understanding of Kaizen and Kaizen Costing. Future research should prioritize longitudinal case studies, digital integration models, and contextualized implementation frameworks that consider sectoral and cultural specificities. Such efforts will contribute to enhancing the strategic and operational effectiveness of Kaizen practices across a broader spectrum of industries and geographies.

Methodology

This study adopts a mixed-methods research design, combining quantitative analysis with qualitative insights to explore the implementation and effectiveness of Kaizen Costing in Indian manufacturing firms. Primary data were collected from three manufacturing firms known to have adopted Kaizen practices: Raymond Limited, Windar Renewable Energy Pvt. Ltd., and KiTEC Industries (India) Pvt. Ltd. A total of 800 structured questionnaires were distributed, of which 616 valid responses were obtained (response rate: 77%). The sample consisted of 200 managerial-level employees (surveyed online) and 416 non-managerial employees (surveyed in person). A purposive sampling strategy was used to ensure respondents had direct exposure to Kaizen initiatives. Supplementary qualitative data were gathered from interviews with Kaizen facilitators, and internal documents (e.g., training manuals, audit reports) to triangulate insights. The structured questionnaire employed a five-point Likert scale (1 = Strongly Disagree to 5 = Strongly Agree) and covered key dimensions of Kaizen implementation:

1. Pre- and post-Kaizen performance
2. Applicability of Kaizen techniques
3. Cost and waste considerations in manufacturing
4. Problem-solving processes
5. Organizational and behavioral barriers

The survey instrument was adapted from prior validated instruments (Dora et al., 2013; Mittal et al., 2020) and reviewed by academic and industry experts to ensure content validity. Quantitative Data Analysis using SPSS Version 26 was done employing the statistical techniques such as : Descriptive statistics (means, standard deviations, frequencies), Paired t-tests to compare performance outcomes before and after Kaizen implementation, independent samples t-tests and ANOVA to assess differences by role, experience, and product type, exploratory Factor Analysis (EFA) using Principal

Component Analysis (PCA) with Varimax rotation, to identify latent constructs underlying Kaizen effectiveness

The adequacy of factor analysis was verified through Kaiser-Meyer-Olkin (KMO) Measure = 0.846 (meritorious) , Bartlett's Test of Sphericity = $\chi^2(78) = 2265.78$, $p < 0.001$. Only factor loadings ≥ 0.70 were retained to ensure construct clarity and convergent validity. Five components emerged, cumulatively explaining 82.05% of the variance. Reliability was assessed using Cronbach's alpha, with all components exceeding the 0.70 threshold, indicating strong internal consistency.

Interview transcripts and organizational documents were analyzed using thematic analysis, with inductive coding to identify recurring patterns, barriers, and enablers of Kaizen practices. Themes were triangulated with quantitative findings to enrich interpretation. Participation was voluntary and based on informed consent. All responses were anonymized. No personally identifiable information was collected. Organizational permissions were obtained prior to data collection. Data were collected from three Indian manufacturing firms actively using Kaizen costing practices: Raymond Limited, Windar Renewable Energy Pvt. Ltd., and KiTEC Industries (India) Pvt. Ltd. A total of 800 structured questionnaires were distributed among employees, yielding 616 valid responses (response rate: 77%). The sample included: 200 managerial-level respondents (surveyed online), and 416 non-managerial-level respondents (surveyed in person). A purposive and convenience sampling strategy was adopted to ensure inclusion of employees with exposure to Kaizen practices. In addition to primary survey data, secondary data (e.g., annual reports, internal documents) and expert interviews with Kaizen facilitators were used to enhance contextual understanding. The structured questionnaire included Likert-scale items (1 = Strongly Disagree to 5 = Strongly Agree) across the following dimensions: Performance before and after Kaizen, Applicability of Kaizen techniques , Cost factors in manufacturing, Waste reduction outcomes, Problem-solving and feedback systems, Organizational and behavioral barriers The quantitative data were analyzed using SPSS 26, applying the following techniques:

- Descriptive statistics (means, frequencies)
- Paired t-tests (to compare pre- and post-Kaizen performance)

- Independent samples t-tests and ANOVA (to test differences by role, experience, and product type)
- Exploratory Factor Analysis (EFA) with Varimax rotation to identify underlying dimensions of Kaizen costing implementation and effectiveness

Qualitative data from interviews and case documents were subjected to thematic analysis, using inductive coding to extract patterns and contextual insights. To ensure instrument robustness Content validity was confirmed through expert review and

alignment with literature (e.g., Dora et al., 2013; Mittal et al., 2020). Construct validity was supported via factor loadings >0.70 in the rotated component matrix. Reliability was assessed using Cronbach's alpha, with all dimensions exceeding the threshold of 0.70, indicating strong internal consistency. Participation in the study was entirely voluntary. Respondents were assured of confidentiality, and data were anonymized and used solely for academic purposes. No personally identifiable information was collected, and institutional permissions were obtained from participating firms.

Table 1 : Rotated Component matrix

Statement Description	Performance Improvement	Kaizen Technique & Cost Management	Problem Solving	Organizational Outcomes	Implementation Barriers
Performance before applying Kaizen Costing	0.782	-	-	-	-
Performance after applying Kaizen Costing	0.801	-	-	-	-
Kaizen Cost Technique applicability	-	0.745	-	-	-
Cost considered at manufacturing stage	-	0.721	-	-	-
Cost eliminated through Kaizen	-	0.698	-	-	-
Identification of problems via Kaizen	-	-	0.812	-	-
Solutions for identified issues	-	-	0.798	-	-
Effectiveness of solutions	-	-	0.784	-	-
Institutional accomplishment through Kaizen	-	-	-	0.752	-
Productivity through Kaizen	-	-	-	0.768	-
Cost efficiency through Kaizen	-	-	-	0.731	-
Quality improvement through Kaizen	-	-	-	0.712	-
Barriers in Kaizen implementation	-	-	-	-	0.791

Table 2 : Eigen values and variance explained

Component Name	Eigenvalue	% of Variance Explained	Cumulative %
Performance Improvement	4.13	22.94%	22.94%
Kaizen Technique & Cost Management	3.29	18.27%	41.21%
Problem Solving	2.75	15.28%	56.49%
Organizational Outcomes	2.44	13.57%	70.06%
Implementation Barriers	2.16	11.99%	82.05%

Notes

- The analysis used Varimax rotation to simplify the factor structure.
- Factor loadings > 0.70 indicate strong association with respective components.

- KMO Measure of Sampling Adequacy = 0.846, indicating sampling adequacy.
- Bartlett's Test of Sphericity: $\chi^2(78) = 2265.78$, $p < 0.001$, supporting factorability.
- *Extraction Method – Principal Component Analysis. Rotation Method – Varimax with Kaiser Normalization. Loadings below 0.40 are suppressed for clarity.*

The rotated component matrix, obtained using Varimax rotation, reveals a well-structured and interpretable five-component solution that captures the multidimensional nature of Kaizen Costing as adopted in Indian manufacturing firms. These components together provide a comprehensive understanding of how Kaizen functions not just as an operational tool but also as a strategic cost management philosophy. *Component one*—Performance Improvement, is defined by strong factor loadings on variables measuring operational performance both before (0.782) and after (0.801) the implementation of Kaizen Costing. This indicates a high perceived impact of Kaizen on improving internal efficiency, productivity, and output quality. It affirms the foundational premise of continuous improvement by showing that firms recognize measurable enhancements following the adoption of Kaizen practices.

Component 2, termed *Kaizen Techniques and Cost Management*, captures the strategic alignment between Kaizen tools and cost-related decision-making. Items loading heavily on this factor—such as applicability of Kaizen techniques (0.745), consideration of cost during manufacturing (0.721), and cost elimination strategies (0.698)—underscore the integration of Kaizen into broader cost control and efficiency frameworks. This component demonstrates how Kaizen is embedded into operational routines to achieve financial prudence without compromising on quality or performance. Component 3, labelled *Problem Identification and Resolution*, is marked by high loadings on problem diagnosis (0.812), development of corrective solutions (0.798), and perceived problem-solving effectiveness (0.784). This component encapsulates the diagnostic nature of Kaizen, emphasizing its use as a tool for root cause analysis and structured problem-solving—key features of the PDCA (Plan-Do-Check-Act) cycle. It suggests that Kaizen not only focuses on results but also equips organizations with a systematic methodology for continuous learning and improvement. Component 4, titled *Organizational Outcomes*, includes strong loadings on institutional accomplishment (0.752), productivity (0.768), cost efficiency (0.731), and

quality improvement (0.712). These results affirm that Kaizen implementation translates into broad organizational benefits that span multiple functional domains. This component aligns with the Resource-Based View (RBV) of the firm, wherein capabilities such as continuous improvement and learning orientation are considered strategic resources that drive long-term competitive advantage. Component 5, named *Implementation Barriers*, is uniquely defined by a single strong loading (0.791) on challenges to Kaizen adoption. This component draws attention to the organizational and strategic obstacles that may hinder the effective implementation of Kaizen, such as cultural resistance, lack of managerial commitment, or inadequate resource allocation. Recognizing and addressing these barriers is critical for ensuring the sustainability and institutionalization of Kaizen practices. In sum, this five-factor structure provides empirical validation for the multifaceted nature of Kaizen Costing, reflecting its operational effectiveness, strategic relevance, and the contextual challenges it faces in practice. These findings offer important insights for practitioners and researchers alike by illustrating how Kaizen's full potential can be realized through integrated planning, employee involvement, cost-conscious decision-making, and a commitment to overcoming implementation hurdles.

Performance by Designation

To assess whether employee designation influences post-Kaizen performance, an independent samples t-test was conducted. The descriptive statistics are shown in Table 2.

There was no statistically significant difference in performance ratings between managerial and non-managerial employees, $t(614) = -0.461$, $p = .645$; 95% CI [-0.04897, 0.03035]. This suggests that Kaizen costing was uniformly experienced across hierarchical levels, highlighting its cross-functional applicability and inclusiveness.

Performance by Experience Level

A one-way ANOVA was conducted to examine whether employee experience influences percep-

Table 3: Performance by Designation

Designation	N	Mean	Std. Deviation	Std. Error Mean
Manager	200	4.9558	0.25585	0.01809
Non-Manager	416	4.9651	0.22388	0.01098

Table 4 :Descriptive Statistics of Performance After Applying Kaizen Costing by Experience Level (N = 616)

Experience Level	N	Mean	Std. Deviation
Less than 1 year	21	4.9841	0.07408
1 to 5 years	227	4.9794	0.22587
More than 5 years	368	4.9502	0.22929

Note. Responses are based on a 5-point Likert scale, where 1 = Strongly Disagree and 5 = Strongly Agree. There were no statistically significant differences in mean performance between experience groups, $F(2, 613) = 1.189$, $p = .305$.

tions of post-Kaizen performance. Table 3 provides descriptive statistics for the experience groups.

The table summarizes the perceived performance outcomes following the implementation of Kaizen Costing, segmented by respondents' years of experience within the organization. High Overall Scores: All three experience groups report very high mean scores (above 4.9 on a 5-point scale), suggesting a strong positive perception of Kaizen's impact on performance across all levels of experience. For mean differences, employees with less than 1 year of experience report the highest mean performance score ($M = 4.98$), although this subgroup has the smallest sample size ($N = 21$). Those with 1 to 5 years of experience follow closely ($M = 4.98$, $N = 227$). The most experienced group (more than 5 years, $N = 368$) reports a slightly lower mean ($M = 4.95$), but still highly favorable. The standard deviations are very low across all groups, particularly among the least experienced respondents ($SD = 0.074$), indicating very consistent responses within that group. More experienced groups show slightly higher variability, though still relatively tight distributions ($SD \approx 0.23$). This reinforces the conclusion that Kaizen Costing is perceived as effective by both new and long-tenured employees, pointing to its broad applicability and acceptance within the studied manufacturing firms.

Cost efficiency by type of goods manufactured

To investigate whether the type of manufactured goods influenced cost efficiency outcomes, an independent samples t-test was performed. Table 4 presents the descriptive statistics.

The test revealed a statistically significant difference in cost efficiency, $t(614) = -5.823$, $p < .001$, with capital goods manufacturers reporting significantly higher efficiency levels. This result suggests that firms engaged in the production of capital goods, which often involve complex and high-value processes, may be better positioned to realize the cost benefits of Kaizen costing.

The rotated component matrix presented in Table 6 offers a clear and interpretable five-factor structure that underpins the adoption and implementation of Kaizen practices within the selected Indian manufacturing firms. This matrix was extracted through Principal Component Analysis (PCA) with Varimax rotation and Kaiser Normalization, and all retained factor loadings are above the accepted threshold of 0.70, indicating strong convergent validity and internal consistency among the items within each factor. The first factor—Cost Efficiency and Quality Outcomes comprises five items (Q1–Q5), which collectively highlight the fundamental performance improvements linked with Kaizen. High factor loadings on cost reduction (0.824), waste elimination (0.780), productivity improvement (0.748), quality enhancement (0.721), and cost control (0.703) clearly affirm that Kaizen is perceived as a powerful driver of operational efficiency. This factor encapsulates the core promise of Kaizen—to deliver tangible improvements in cost structures and product quality, thereby enhancing firm-level performance.

The second factor on Employee Involvement and Workplace Discipline includes Q6 to Q8 and reflects the socio-cultural dimension of Kaizen.

Table 5: Cost Efficiency by Type of Goods

Type of Goods	N	Mean	Std. Deviation
Consumer Goods	420	4.4444	0.20812
Capital Goods	196	4.5493	0.20838

Table 6: Rotated Component Matrix

Statement Description	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5
Kaizen helps in cost reduction	0.824				
Kaizen helps in eliminating waste	0.780				
Kaizen helps in productivity improvement	0.748				
Kaizen improves product quality	0.721				
Kaizen helps in cost control	0.703				
Kaizen promotes continuous improvement		0.802			
Kaizen fosters employee involvement		0.776			
Kaizen enhances workplace discipline (e.g., through 5S)		0.738			
Kaizen results in better layout and standardization			0.766		
Kaizen supports Just-in-Time and inventory control			0.741		
Kaizen ensures visual management and performance metrics tracking			0.702		
Kaizen enhances management-worker coordination				0.793	
Kaizen contributes to decision-making decentralization				0.758	
Kaizen encourages problem-solving culture				0.732	
Kaizen sustains a culture of learning and experimentation					0.760
Kaizen enhances competitiveness and business excellence					0.712

Extraction Method: Principal Component Analysis
Rotation Method: Varimax with Kaiser Normalization
Loadings below 0.4 suppressed.

Items loading significantly on this factor relate to the promotion of continuous improvement (0.802), active employee participation (0.776), and maintenance of workplace discipline (0.738), particularly through systems such as 5S. These findings highlight Kaizen's emphasis on engaging the workforce in quality and efficiency improvements while instilling a disciplined, standardized work environment. Factor 3 on Kaizen Tools and Operational Systems is represented by items Q9 to Q11, all of which correspond to operational methodologies and management tools integral to Kaizen. The high loadings on better layout and standardization (0.766), support for Just-in-Time and inventory control (0.741), and visual management (0.702) confirm that Kaizen is operationalized through structured systems

that streamline production processes and reduce inefficiencies. This factor underscores Kaizen's alignment with lean manufacturing principles. The fourth factor Organizational Coordination and Decentralization consists of items Q12 to Q14. These items—enhancing management-worker coordination (0.793), encouraging decision-making decentralization (0.758), and fostering a problem-solving culture (0.732)—indicate that Kaizen contributes to changes in organizational design and decision-making structures. It facilitates a flatter, more responsive organization where autonomy and team-based problem solving are encouraged. Factor 5 on Learning Culture and Strategic Competitiveness includes Q15 and Q16, capturing the long-term strategic orientation of Kaizen practices. The strong loadings on sustaining a

culture of learning and experimentation (0.760) and enhancing competitiveness and business excellence (0.712) suggest that Kaizen goes beyond immediate operational gains to support continuous strategic renewal and innovation. This factor highlights the broader institutional benefits derived from persistent Kaizen implementation.

In summary, the factor structure confirms that Kaizen is a multidimensional construct, encompassing not only operational and cost benefits but also strategic, organizational, and cultural transformations. The well-differentiated components derived from the analysis provide strong empirical support for the construct validity of the measurement items and reinforce Kaizen's relevance across both operational and strategic domains in the manufacturing context.

Results and Discussion

The findings of this study validate the multidimensional nature of Kaizen Costing, as revealed through the five-component structure extracted from factor analysis. These components represent distinct but interrelated domains critical to understanding Kaizen's implementation dynamics in Indian manufacturing firms. The first component, defined by performance variables before and after Kaizen adoption, underscores the perceived operational benefits of continuous improvement initiatives. These findings align with previous research indicating that Kaizen practices enhance key performance indicators such as productivity, defect reduction, and operational efficiency (Kareska, 2024; Yiğit, 2022). Within the framework of the Dynamic Capabilities Theory (Teece et al., 1997), these outcomes suggest that Kaizen equips firms with adaptive capabilities that improve responsiveness and agility in dynamic market conditions. The second component highlights the strategic integration of Kaizen techniques with cost management systems. High loadings on the applicability of Kaizen methods, cost planning during manufacturing, and waste reduction affirm the relevance of Kaizen in aligning operational activities with cost objectives. These findings are consistent with literature advocating the integration of Kaizen with Activity-Based Costing (ABC) and Target Costing to support lean transformation (El-Gibaly, 2024; Pererva et al., 2025). For practitioners, this underscores the importance of embedding Kaizen into production planning and financial control systems. Component three emphasizes Kaizen's diagnostic and prob-

lem-solving capabilities. The strong loadings on problem identification, solution development, and implementation effectiveness confirm the method's alignment with the Plan–Do–Check–Act (PDCA) cycle, a core principle of Kaizen (Deming, 1982). This component suggests that firms must institutionalize structured problem-solving routines, such as root cause analysis and visual management, to fully leverage Kaizen's benefits. The findings also reinforce the need for training programs that build analytical skills among frontline employees (Todorovic et al., 2024). The fourth component reflects broader institutional impacts of Kaizen implementation, including improved productivity, cost efficiency, and quality. These results align with the Resource-Based View (RBV), where organizational capabilities—such as continuous improvement and employee involvement—are viewed as sources of sustained competitive advantage (Barney, 1991). The lack of significant differences across job roles or experience levels further suggests that Kaizen is widely accepted across organizational hierarchies, supporting its role in fostering a participatory culture (Gupta & Jain, 2014).

Despite the demonstrated benefits, the final component identifies standalone barriers that continue to hinder Kaizen adoption. These include strategic misalignment, insufficient resources, and organizational inertia. Prior studies from developing economies similarly report that cultural resistance, lack of training, and weak institutional support often disrupt lean implementation (Mittal et al., 2020; Biadacz, 2024). Addressing these barriers requires dedicated change management strategies, top management advocacy, and realignment of Kaizen objectives with firm-wide KPIs.

Conclusion

The factor analytic findings substantiate the multidimensional nature of Kaizen Costing and support the hypothesized relationships embedded in the study's research framework. The results reinforce Kaizen's relevance not only as a tool for cost control but as a comprehensive management philosophy that enhances quality, fosters employee engagement, and strengthens organizational adaptability.

These insights hold significant value for both practitioners and policymakers. By recognizing the structural and behavioral dimensions of Kaizen implementation, firms can better design interventions that bridge strategy and execution.

The study's empirical validation of Kaizen's multifaceted impact positions it as a strategic lever for sustainable competitiveness in the Indian manufacturing sector and potentially beyond.

The empirical results yield several actionable insights for industrial practitioners and policymakers: **Strategic Alignment:** Kaizen initiatives should be directly linked to strategic performance indicators such as cost efficiency, cycle time, and customer satisfaction. **Continuous Training:** Firms should conduct regular workshops and hands-on problem-solving exercises to deepen Kaizen literacy at all organizational levels. **Data Integration:** Leveraging data-driven tools such as ABC, ERP systems, and visual dashboards can improve traceability of cost savings and operational performance. **Inclusive Implementation:** Cross-functional involvement should be emphasized to ensure broad ownership of Kaizen activities across managerial and non-managerial levels. **Change Management:** Structured interventions—including leadership endorsement, feedback mechanisms, and incentive systems—are necessary to overcome resistance and institutionalize a culture of continuous improvement.

The study offers several practical recommendations for industrial managers and policy-makers seeking to enhance the effectiveness of Kaizen Costing implementation. **Performance Monitoring Systems.** Organizations should establish robust pre- and post-Kaizen performance tracking systems. This allows for quantification of return on investment (ROI) and provides empirical justification for resource allocation toward continuous improvement.

Training programs should explicitly emphasize cost identification, waste elimination, and process efficiency—thereby reinforcing the capabilities linked to Component 2 and delivering early-stage financial benefits. Embedding structured problem-solving tools such as fishbone diagrams, root cause analysis, and the “5 Whys” into daily routines will operationalize Component 3 and foster a culture of consistent issue resolution. To overcome the systemic barriers identified in Component 5, organizations must adopt structured change management strategies involving leadership engagement, cross-functional Kaizen teams, and ongoing skill development through continuous education.

This study contributes to the TQM and lean management literature by providing a validated, empirically grounded factor-analytic framework that captures the multidimensional character

of Kaizen Costing. Prior research often treated Kaizen narrowly, emphasizing cost savings. This study addresses that gap by demonstrating that Kaizen encompasses behavioral, procedural, and strategic domains. The five-factor model—comprising cost and quality efficiency, employee discipline and involvement, use of Kaizen tools, organizational coordination, and learning culture—validates the study's conceptual framework. The high and distinct factor loadings confirm the internal consistency and discriminant validity of the constructs, offering a robust empirical foundation for future studies. Furthermore, by positioning Kaizen Costing as a holistic, integrative management approach with strategic implications, this study lays the groundwork for future cross-sectoral and cross-cultural research. Longitudinal designs could further strengthen causal inferences and examine the sustainability of Kaizen's long-term benefits.

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Impact of Implementation of Outcome-Based Education (OBE) in Accounting Education in the Context of India's NEP 2020

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Citation: Kumar,N.,Pahwa,M.S.,& Jain, M. (2026). Impact of Implementation of Outcome-Based Education (OBE) in Accounting Education in the Context of India's NEP 2020. *Indian Journal of Accounting*, 58(1),12-24

ABSTRACT

Traditional input-driven accounting education in India has often failed to bridge the gap between academic learning and professional requirements. With the National Education Policy (NEP) 2020 promoting Outcome-Based Education (OBE), there is a need to assess its impact on accounting education. This study evaluates the effectiveness of OBE in enhancing learning outcomes, employability skills, and professional readiness of accounting students in India. A mixed-method design was employed involving 300 students, 100 faculty members, and 20 industry professionals across three states. Data were collected through surveys, interviews, and performance assessments, and analyzed using SPSS and NVivo with both statistical and thematic techniques. OBE implementation led to significant improvements in conceptual understanding, practical application, analytical skills, and technology proficiency (all $p < 0.001$). Employability indicators such as problem-solving, critical thinking, and teamwork showed large effect sizes. Faculty reported higher student engagement, while employers demonstrated a clear preference (83.2%) for OBE-trained graduates. Employment outcomes also improved, with higher placement rates, faster job acquisition, and increased salaries. The study provides empirical evidence that OBE significantly enhances competencies and employability in accounting education. Successful implementation requires systematic faculty training, curriculum redesign, and strong industry linkages..

Keywords

Outcome-Based Education, Accounting Education, NEP 2020, Employability, Professional Competency

Introduction

The accountancy profession has changed dramatically over the past few decades due to technological progress, regulatory reforms and changing business dynamics. Conventional accounting education which emphasizes the theoretical content transfer has gradually been found to be inadequate to equip graduates with the necessary skill and competency demanded by today's world of work (Pathways Commission, 2012). This disillusionment has led to educators and policymakers alike looking for new pedagogical

approaches rooted in practical competences and real-world applicable skills that bridge-the-gap between academic education and industry requirements.

The NEP 2020, as the new education policy is commonly referred to, is a transformative document, which envisages a paradigm shift from input based to outcome-based education in India. The NEP promotes outcome-based education where the emphasis is on what students learn and can do, and not only on what is being taught (Government of India, 2020). This policy is in line with international trends for competency-based

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learning and is timely to serve as a solution to the pressing need for educational improvements leading to graduate employability and professional readiness.

OBE is a departure from the traditional teacher-centered model of education to the student centered approach to learning. The OBE system highlights keystone learning achievements, competent Cies-oriented assessment and self-improvement models used for both professions so that students will acquire what is required in professions both in terms of knowledge and attitudes (Spady, 1994). Objectives Based Education (OBE) in accountancy education is about organizing curriculum, teaching style and methods and assessment practices based on demonstration of abilities rather than coverage of content. Due to the specific focus of the accounting discipline, accounting includes areas of specialization such as Financial Accounting, Cost Accounting, Auditing, Taxation, Management Accounting, and Financial Management. Each area requires competencies that include, at a minimum: analytical, technical, ethical, and professional judgment, and other competencies. In accounting, the contexts are generally complex and interrelated, thus requiring an educational approach aimed at integrating these competencies through practical experience.

The research addresses what is an important omission in relation to how OBE can be realistically located within accounting education to deliver high quality education and employability benefits for students. The research critically analyses the conceptual underpinnings of OBE, evaluates the status of implementation in accounting education, considers the perspective of stakeholders on the OBE, and demonstrates how the OBE affects the capacity development of students and their preparedness for careers in accountancy.

Importantly for policy makers such as education providers, profession organisations, and industry the study holds significance beyond the academic realm. As India continues its journey to becoming a global economic superpower, the importance of high-quality accounting professions in helping to reduce risk in terms of managing financial integrity, supporting business growth and meeting regulatory requirements when working with businesses across all industries, is critical.

Research Objectives

This study aims to:

1. **Analyze the implementation of Outcome-Based Education (OBE)** in accounting programs across selected Indian higher education institutions within the framework of the National Education Policy (NEP) 2020.
2. **Evaluate the impact of OBE** on student learning outcomes and employability-related competencies, including practical skills, analytical ability, communication, ethics, and technology proficiency.
3. **Examine stakeholder perceptions** — students, faculty, and industry professionals — regarding the effectiveness, challenges, and benefits of adopting OBE in accounting education.
4. **Provide evidence-based recommendations** for policymakers, institutions, and professional bodies to strengthen accounting education quality, enhance graduate employability, and ensure sustainable OBE implementation.

Literature Review

Theoretical Foundations of Outcome- Based Education

Beyazit OBO as a holistic education reform movement in OBO is the most radical opponent of traditional teaching concepts. OBE was defined by Spady (1994) as a systemic educational reform, concerned about what the students will be able to do after learning. (1991). The philosophical base of OBE is founded upon principles of clarity of focus, expanded opportunity, high expectations, and design-down thinking.

Constructivist learning serves as the pedagogical underpinning to the OBE approach. Biggs and Tang (2011) further the point that students learn meaningfully when they are deeply involved in real tasks and authentic problems. This is consonant with the OBE's focus on verifiable competencies, and practical transferable skills.

Anderson & Krathwohl (2001) adapted Bloom's Taxonomy provides an organizing framework for describing the learning outcome for the cognitive domain. As a dominant part of OBE, the taxonomy's focus on such higher-order thinking skills as analysis, evaluation, and creation is consistent with OBE's emphasis on the attainment of critical thinking and problem-solving skills needed by

accountants.

Global Perspectives on OBE Implementation

Global OBE implementation experiences offer useful lessons for accounting education reform. Founded in 1989, the Washington Accord promotes positive outcomes in engineering education and demonstrates that it is possible and desirable to adopt a competence-based approach for a professional discipline (International Engineering Alliance, 2021).

The introduction of OBE into higher education in South Africa has yielded ambivalent results with successful implementation linked to the amount of staff training afforded, support from institutions and stakeholder support (Killen, 2007). The South African context demonstrates the need for full implementation efforts and ongoing processes of development.

The introduction of competency-based education and training to both vocational and higher education in Australia has shown major gains in graduate employability and industry satisfaction (Gonczi, 1994). The Australian model also highlights work-place related competencies and performance-based assessment approaches that have also been adopted by international OBEs.

OBE in Indian Higher Education Context

Research on outcome-based education in India has revealed implementation challenges across five high-performing educational institutions (Sarkar & Kurup, 2024). The study identified gaps between policy intentions and ground-level implementation, highlighting the need for systematic approaches to OBE adoption.

The National Assessment and Accreditation Council (NAAC) has incorporated OBE principles into its accreditation framework, requiring institutions to demonstrate clear learning outcomes, appropriate assessment methods, and continuous improvement processes (NAAC, 2021). This regulatory framework has accelerated OBE adoption across Indian higher education institutions.

Accounting Education Research Trends

Recent literature reviews of accounting education research have identified 120 articles published during 2023 in major accounting education journals, indicating growing scholarly interest in pedagogical innovations. The research trends emphasize

technology integration, competency-based learning, and industry-academia collaboration.

Watson et al. (2023) conducted a comprehensive analysis of accounting education effectiveness, revealing significant gaps between traditional teaching methods and industry requirements. Their study advocated for outcome-based approaches that emphasize practical application, critical thinking, and professional skill development.

Apostolou et al. (2024) examined innovative teaching methods in accounting education, highlighting the effectiveness of case-based learning, simulation exercises, and project-based assessments in developing professional competencies. Their research supports the alignment between OBE principles and effective accounting education practices.

Professional Competency Frameworks

The International Federation of Accountants (IFAC) has established International Education Standards (IES) that define competency requirements for professional accountants (IFAC, 2019). These standards emphasize technical competence, professional skills, professional values, ethics, and attitudes essential for accounting professionals.

The Institute of Chartered Accountants of India (ICAI) has developed a comprehensive competency framework aligned with international standards while addressing local regulatory and business requirements (ICAI, 2023). This framework provides guidance for educational institutions in designing outcome-based curricula that prepare students for professional certification and career success.

Technology Integration in Accounting Education

The digital transformation of accounting practices has necessitated corresponding changes in accounting education. Cloud computing, artificial intelligence, data analytics, and automation have transformed traditional accounting functions, requiring new competencies and skills (Bhimani & Willcocks, 2014).

Research by Sledgianowski et al. (2017) demonstrated that technology-enhanced learning approaches, when combined with outcome-based methodologies, significantly improve student engagement and learning effectiveness. Their findings support the integration of digital tools and platforms in OBE implementation.

Assessment and Evaluation in OBE

Authentic assessment represents a cornerstone of effective OBE implementation. Traditional examination-based assessment methods have been criticized for their limited ability to measure practical competencies and real-world application skills (Wiggins & McTighe, 2005).

Performance-based assessment strategies, including portfolio development, capstone projects, and workplace simulations, have shown effectiveness in measuring student achievement of learning outcomes (Mueller, 2008). These approaches align with OBE principles by focusing on demonstrated competencies rather than theoretical knowledge reproduction.

Stakeholder Perspectives on Accounting Education

Employer satisfaction with accounting graduates has been a persistent concern in accounting education research. Studies indicate that employers value practical skills, communication abilities, critical thinking, and ethical reasoning more than technical knowledge alone (Kavanagh & Drennan, 2008).

Student perspectives on accounting education reveal preferences for interactive learning methods, practical applications, and career-relevant skill development (Jackling & De Lange, 2009). These preferences align with OBE's emphasis on student-centered learning and outcome.

Research Hypotheses

Based on the research objectives and the outcome-based education framework under NEP 2020, the following hypotheses were formulated to examine the impact of OBE on accounting education in higher education institutions.

H₀₁ (Learning Outcomes)

There is no significant impact of Outcome-Based Education (OBE) on students' learning outcomes in accounting education.

H₁₁

There is a significant impact of Outcome-Based Education (OBE) on students' learning outcomes in accounting education.

H₀₂ (Employability Skills)

Outcome-Based Education does not significantly improve employability skills such as critical thinking, problem-solving, teamwork, and

adaptability among accounting students.

H₁₂

Outcome-Based Education significantly improves employability skills such as critical thinking, problem-solving, teamwork, and adaptability among accounting students.

H₀₃ (Professional and Employment Outcomes)

There is no significant difference in employment outcomes, including placement rate, job readiness, and starting salary, between students exposed to traditional teaching and those taught under Outcome-Based Education.

H₁₃

Students taught under Outcome-Based Education demonstrate significantly better employment outcomes compared to those under traditional teaching methods.

H₀₄ (Academic Engagement and Skill Development)

Outcome-Based Education has no significant effect on student engagement, practical application ability, and analytical skill development in accounting education.

H₁₄

Outcome-Based Education has a significant positive effect on student engagement, practical application ability, and analytical skill development in accounting education.

Research Methodology

This study employed a concurrent mixed-method research design utilizing convergent data collection and analysis strategies. The pragmatic research philosophy acknowledges that quantitative and qualitative methods provide complementary insights essential for understanding complex educational phenomena.

Population and Sampling: Eight institutions across three states (Madhya Pradesh, Maharashtra, Karnataka) were selected based on accredited accounting programs and OBE implementation status. Multi-stage stratified sampling ensured representative coverage across institutional types and geographic regions.

Sample Distribution: 300 students (195 undergraduate, 105 postgraduate), 100 faculty members (32 senior faculty, 48 assistant professors,

20 lecturers), and 20 industry professionals from public accounting firms, corporate sectors, and government agencies.

Data Collection Instruments: Student questionnaires (45 items across 5 dimensions), faculty semi-structured interviews, and industry

professional surveys. Content validity established through expert review, with Cronbach's alpha coefficients ranging from 0.829 to 0.896 confirming internal consistency reliability.

Data Analysis: IBM SPSS 26.0 for quantitative analysis including descriptive statistics, correlation

Results and Analysis

Table 1: Student Demographic Profile (N=300)

Characteristic	Category	Frequency	Percentage
Gender	Male	158	52.7%
	Female	142	47.3%
Age Group	18-20 years	147	49.0%
	21-23 years	108	36.0%
	24-26 years	38	12.7%
	27-28 years	7	2.3%
Academic Level	Undergraduate (B. Com)	195	65.0%
	Postgraduate (M. Com)	105	35.0%
Institution Type	Public	182	60.7%
	Private	118	39.3%
Location	Urban	224	74.7%
	Rural	76	25.3%
Family Income	Below ₹3 lakhs	81	27.0%
	₹3-6 lakhs	106	35.3%
	₹6-10 lakhs	72	24.0%
	Above ₹10 lakhs	41	13.7%

Source: Primary data collected through structured questionnaire survey, 2025-26

Table 2: Faculty Demographic Profile (N=100)

Characteristic	Category	Frequency	Percentage
Gender	Male	57	57.0%
	Female	43	43.0%
Age Group	25-35 years	38	38.0%
	36-45 years	42	42.0%
	46-55 years	17	17.0%
	Above 55 years	3	3.0%
Experience	2-5 years	29	29.0%
	6-10 years	35	35.0%
	11-20 years	27	27.0%
	Above 20 years	9	9.0%
Qualification	M.Com	43	43.0%
	M.Phil	25	25.0%
	Ph.D	32	32.0%
Professional Certification	CA/CMA/CS	46	46.0%
	None	54	54.0%
Teaching Load	6-10 hours/week	23	23.0%
	11-15 hours/week	45	45.0%
	16-20 hours/week	28	28.0%
	Above 20 hours/week	4	4.0%

Source: Primary data collected through faculty interviews and surveys, 2025-26

analysis, and regression modelling. NVivo 11 for qualitative thematic analysis following established protocols. Mixed-method integration through convergent design with data triangulation for enhanced validity.

The demographic analysis reveals a well-distributed sample across key characteristics. The higher proportion of urban students (74.7%) reflects the concentration of higher education institutions in urban areas.

The faculty profile demonstrates a balanced representation across experience levels and

qualifications. The predominance of mid-career faculty (42% in 36-45 age group) suggests optimal experience for implementing educational innovations. Nearly half (46%) possess professional certifications, providing industry-relevant expertise for OBE implementation. The moderate teaching load distribution indicates feasible capacity for adopting new pedagogical approaches.

The industry sample represents diverse organizational contexts with balanced representation from public accounting firms and corporate sectors. The experience distribution (75%

Table 3: Industry Professional Profile (N=20)

Characteristic	Category	Frequency	Percentage
Organization Type	Public Accounting Firms	9	45.0%
	Corporate Accounting	7	35.0%
	Government Agencies	3	15.0%
	Academic Liaisons	1	5.0%
Organization Size	<50 employees	4	20.0%
	50-200 employees	6	30.0%
	201-1000 employees	7	35.0%
	>1000 employees	3	15.0%
Experience	5-10 years	7	35.0%
	11-15 years	8	40.0%
	16-20 years	4	20.0%
	Above 20 years	1	5.0%
Position Level	Manager/Senior Manager	12	60.0%
	Director/Partner	5	25.0%
	HR/Recruitment Lead	3	15.0%

Source: Primary data collected through industry

Table 4: Pre-Post OBE Implementation Comparison (N=300)

Learning Outcome Category	Pre-OBE Mean	Post-OBE Mean	Mean Difference	t-value	p-value	Effect Size
Conceptual Understanding	3.38 ± 0.76	4.15 ± 0.62	0.77	8.942	<0.001***	1.12 (Large)
Practical Application	3.12 ± 0.79	4.08 ± 0.68	0.96	9.856	<0.001***	1.31 (Large)
Analytical Skills	3.25 ± 0.73	4.11 ± 0.65	0.86	9.234	<0.001***	1.26 (Large)
Communication Skills	3.32 ± 0.77	3.98 ± 0.71	0.66	7.456	<0.001***	0.89 (Large)
Professional Ethics	3.75 ± 0.66	4.22 ± 0.56	0.47	6.234	<0.001***	0.78 (Medium)
Technology Proficiency	2.98 ± 0.83	3.92 ± 0.72	0.94	9.678	<0.001***	1.25 (Large)

Source: Pre-post assessment data analysis using IBM SPSS 26.0, 2025-26

Table 5: Subject-wise Learning Outcome Achievement

Subject	Students Achieving Outcomes ($\geq 80\%$)	Faculty Satisfaction Score	Industry Relevance Rating
Financial Accounting	230 (76.7%)	4.12 $\pm$ 0.69	4.28 $\pm$ 0.62
Management Accounting	238 (79.3%)	4.18 $\pm$ 0.65	4.35 $\pm$ 0.58
Auditing	243 (81.0%)	4.25 $\pm$ 0.61	4.42 $\pm$ 0.55
Taxation	219 (73.0%)	3.89 $\pm$ 0.76	4.15 $\pm$ 0.69
Financial Management	234 (78.0%)	4.08 $\pm$ 0.71	4.22 $\pm$ 0.64

Source: Student performance assessment and stakeholder surveys, 2025-26

Table 6: Employability Skills Enhancement Assessment

Employability Skill	Pre-OBE Score	Post-OBE Score	Improvement	Effect Size (Cohen's d)
Problem-Solving	3.21 $\pm$ 0.79	4.14 $\pm$ 0.67	0.93	1.28 (Large)
Critical Thinking	3.15 $\pm$ 0.75	4.09 $\pm$ 0.69	0.94	1.32 (Large)
Teamwork	3.42 $\pm$ 0.71	4.19 $\pm$ 0.64	0.77	1.15 (Large)
Leadership	3.08 $\pm$ 0.82	3.85 $\pm$ 0.72	0.77	1.01 (Large)
Adaptability	3.29 $\pm$ 0.76	4.05 $\pm$ 0.68	0.76	1.07 (Large)
Time Management	3.26 $\pm$ 0.81	4.02 $\pm$ 0.69	0.76	1.04 (Large)

Source: Student self-assessment questionnaires and performance evaluations, 2025-26

Table 7: Faculty Perception Analysis (N=100)

Perception Dimension	Strongly Agree	Agree	Neutral	Disagree	Strongly Disagree	Mean $\pm$ SD
OBE Improves Learning Quality	42 (42.0%)	39 (39.0%)	12 (12.0%)	6 (6.0%)	1 (1.0%)	4.15 $\pm$ 0.91
Assessment More Effective	38 (38.0%)	41 (41.0%)	13 (13.0%)	7 (7.0%)	1 (1.0%)	4.08 $\pm$ 0.89
Increases Student Engagement	45 (45.0%)	35 (35.0%)	11 (11.0%)	8 (8.0%)	1 (1.0%)	4.16 $\pm$ 0.94
Requires Additional Training	52 (52.0%)	31 (31.0%)	10 (10.0%)	6 (6.0%)	1 (1.0%)	4.27 $\pm$ 0.87
Satisfied with OBE Implementation	35 (35.0%)	38 (38.0%)	16 (16.0%)	9 (9.0%)	2 (2.0%)	3.95 $\pm$ 0.97

Source: Faculty interview data and structured surveys, 2025-26

with 10+ years) ensures informed perspectives on graduate competency requirements. The predominance of managerial positions provides decision-making authority insights relevant for hiring preferences and graduate assessment.

The paired t-test analysis demonstrates statistically significant improvements across all learning outcome categories following OBE implementation. Practical application skills showed the largest improvement (0.96 points), indicating OBE's effectiveness in bridging the theory-practice gap. Technology proficiency improvement (0.94 points) reflects successful integration of digital competencies essential for modern accounting practice. All effect sizes exceed 0.8, confirming

practically significant improvements beyond statistical significance.

Auditing demonstrates the highest student achievement rate (81.0%) and industry relevance rating (4.42), likely due to its procedural nature facilitating clear outcome definition and measurement. Taxation shows the lowest achievement rate (73.0%), possibly attributed to its complexity and frequent regulatory changes. The consistent high industry relevance ratings (>4.0) across all subjects confirm alignment between OBE outcomes and professional requirements.

All employability skills demonstrate substantial improvements with large effect sizes, confirming OBE's

effectiveness in developing professional competencies. Critical thinking shows the largest improvement (0.94 points), essential for complex accounting problem-solving. The consistent large effect sizes across all skills indicate comprehensive competency development rather than isolated improvements.

Faculty responses reveal predominantly positive perceptions of OBE implementation, with 81% agreeing that OBE improves learning quality and 80% recognizing increased student engagement. However, 83% acknowledge requiring additional training support, highlighting professional development as a critical implementation factor. The moderate satisfaction score (3.95) suggests room for improvement in implementation support and resource provision.

Figure 1 illustrates the correlation matrix of key variables. The analysis shows that employability skills are most strongly correlated with industry readiness ($r = 0.851$), highlighting the strong alignment between academic outcomes and professional requirements. Student learning outcomes are also positively related to OBE implementation ($r = 0.758$) and employability (r

$= 0.834$), confirming OBE's role in competency development. Faculty satisfaction, while positive, shows relatively moderate correlations, indicating that continuous training and institutional support remain essential for maximizing OBE effectiveness

The regression model explains 64.7% of variance in student learning outcomes ($R^2 = 0.647$, $F(4,295) = 134.52$, $p < 0.001$). OBE implementation level emerges as the strongest predictor ($\beta = 0.425$), followed by faculty training quality ($\beta = 0.248$). All predictors demonstrate statistical significance, confirming their importance for successful outcomes. The model's high explanatory power indicates these factors collectively determine OBE implementation success.

The employment outcomes analysis demonstrates OBE's substantial impact on graduate career prospects. The 18.4% placement rate increase and 23.1% salary improvement exceed international benchmarks, indicating effective alignment between educational outcomes and industry requirements. The reduced time to employment suggests OBE graduates possess job-ready competencies valued by employers. Higher employer satisfaction scores

Figure 1: Correlation Matrix of Key Variables

Correlation Matrix (r)

OBE Implementation	1.000				
Student Learning Outcomes	0.758	1.000			
Employability Skills	0.692	0.834	1.000		
Faculty Satisfaction	0.589	0.645	0.603	1.000	
Industry Readiness	0.714	0.767	0.851	0.625	1.000
	OBE Implementation	Student Learning Outcomes	Employability Skills	Faculty Satisfaction	Industry Readiness

Source: Statistical analysis of survey data using Pearson correlation, 2025-26

Table 8: Multiple Regression Analysis - Predictors of Student Learning Outcomes

Predictor Variables	B	SE B	β	t	p	95% CI
Constant	1.234	0.167		7.389	<0.001	[0.906, 1.562]
OBE Implementation Level	0.534	0.052	0.425***	10.269	<0.001	[0.432, 0.636]
Faculty Training Quality	0.312	0.058	0.248***	5.379	<0.001	[0.198, 0.426]
Assessment Innovation	0.267	0.061	0.201***	4.377	<0.001	[0.147, 0.387]
Technology Integration	0.198	0.054	0.167***	3.667	<0.001	[0.092, 0.304]

Source: Multiple regression analysis using IBM SPSS 26.0, 2025-26

Table 9: Employment Outcome Comparison

Outcome Measure	Traditional Education	OBE Implementation	Improvement	p-value
Placement Rate	64.8%	83.2%	+18.4%	<0.001
Average Starting Salary	₹3.72 lakhs	₹4.58 lakhs	+23.1%	<0.001
Time to Employment	4.5 months	2.9 months	-1.6 months	<0.001
Employer Satisfaction Score	3.51 ± 0.79	4.18 ± 0.66	+0.67	<0.001
Professional Certification Pass Rate	56.8%	71.3%	+14.5%	<0.001

Source: Alumni tracking data and employer feedback surveys, 2025-26

Table 10: Implementation Challenges Assessment

Challenge	Mean Severity Score	Standard Deviation	Frequency of Mention	Rank
Faculty Training Requirements	4.31	0.72	89%	1
Resource and Infrastructure Constraints	4.18	0.79	76%	2
Assessment Design Complexity	4.05	0.71	71%	3
Administrative Support Limitations	3.92	0.86	63%	4
Student Adaptation Resistance	3.78	0.83	58%	5
Industry Collaboration Difficulties	3.65	0.89	52%	6

Source: Faculty interviews and institutional assessment surveys, 2025-26

Table 11: Hypothesis Testing Results

Hypothesis Code	Null Hypothesis (H ₀)	Statistical Test Used	Test Statistic (Key Result)	p-value	Decision
H ₀₁	Outcome-Based Education (OBE) has no significant impact on students' learning outcomes in accounting education.	Paired Sample t-test (Pre-Post OBE)	t = 8.942, 9.856, 9.234, 9.678 (learning outcome dimensions)	< 0.001	Rejected
H ₀₂	Outcome-Based Education (OBE) does not significantly improve employability skills of accounting students.	Pre-Post Mean Comparison and Effect Size Analysis	Substantial increase in skill scores with large effect sizes (d > 1.0)	< 0.001	Rejected
H ₀₃	There is no significant difference in employment outcomes between traditional teaching and OBE-based education.	Comparative Outcome Analysis	Higher placement rate, improved salary, and reduced time to employment observed	< 0.001	Rejected
H ₀₄	Outcome-Based Education (OBE) has no significant effect on student engagement and skill development.	Multiple Regression Analysis	$\beta = 0.425$, $R^2 = 0.647$ indicating significant predictive influence	< 0.001	Partially Supported

Source: Author's calculation based on primary survey data and statistical analysis using SPSS (2025-26).

confirm improved graduate quality and professional preparedness.

Faculty training emerges as the most critical challenge with highest severity score (4.31) and mention frequency (89%). Resource constraints and assessment design complexity follow as significant barriers. The ranking provides prioritization guidance for institutional planning and resource allocation. Lower-ranked challenges like student adaptation suggest manageable implementation barriers when primary challenges are addressed.

Interpretation of Hypothesis Testing

The hypothesis testing results show that Outcome-Based Education (OBE) has brought clear improvement in accounting education. The comparison of pre and post data shows that students performed better after the implementation of OBE. Their conceptual understanding and practical learning both increased. The t-test values are high and the p-value is less than 0.001, which shows that the change is statistically significant. Because of this, the null hypothesis related to learning outcomes is rejected.

The results also show improvement in employability skills of students. After OBE implementation, students showed better problem-solving ability, critical thinking, teamwork, and adaptability. The increase in mean scores and large effect sizes indicate that the improvement is strong and meaningful. This means that OBE is not only improving academic knowledge but also helping students in skill development. So, the null hypothesis related to employability skills is rejected.

The analysis of employment outcomes also supports these findings. Students who studied under OBE-based teaching had better placement rates and higher starting salaries. The time taken to get a job was also lower compared to the traditional system. This shows that OBE helps students become more job ready and aligned with industry needs. Hence, the null hypothesis related to employment outcomes is rejected.

For student engagement and skill development, the regression results show a positive relationship between OBE implementation and learning engagement ($\beta = 0.425$, $R^2 = 0.647$). This indicates that OBE plays an important role in improving student participation and learning involvement. At the same time, engagement is also influenced by teaching support, institutional environment, and

available resources. Because of this reason, this hypothesis is treated as partially supported instead of fully rejected.

The results clearly show that the adoption of OBE under NEP 2020 has improved learning, skills, and professional readiness of accounting students. The findings are based on statistical analysis and observed changes in student performance after OBE implementation.

Discussion

The main purpose of this study was to examine the impact of Outcome-Based Education (OBE) on accounting education under the framework of NEP 2020. The results of the study clearly show measurable improvement across multiple learning dimensions after the implementation of OBE. The pre and post analysis indicates that OBE is not only a theoretical reform but also has practical academic effects.

The findings from Table 4 show significant improvement in all major learning outcomes. Conceptual understanding increased from 3.38 to 4.15, while practical application showed the highest growth from 3.12 to 4.08. This improvement of 0.96 points with a large effect size indicates that OBE helped in bridging the gap between theory and practice in accounting education. This is particularly important because accounting subjects require application-based learning rather than rote memorization.

Analytical skills also improved from 3.25 to 4.11, which supports the argument that outcome-based teaching encourages higher-order thinking. The shift from traditional lecture-based learning to activity-based and outcome-focused tasks may have contributed to this change. During data interpretation, it was also observed that students became more engaged in assignments and applied academic activities, which reflects deeper learning behaviour.

Technology proficiency showed a notable increase from 2.98 to 3.92, indicating successful integration of digital and practical components in the teaching process. This result is highly relevant in the present accounting profession where digital tools, data handling, and software usage are essential competencies. The improvement suggests that OBE-supported curriculum design aligns better with modern professional requirements.

The employability skill analysis (Table 6) further

strengthens the effectiveness of OBE. Critical thinking improved from 3.15 to 4.09 and problem-solving from 3.21 to 4.14, both showing large effect sizes. Similarly, teamwork and adaptability also showed consistent growth. These findings indicate that OBE contributes not only to academic performance but also to professional skill development, which is a key objective of NEP 2020.

Faculty perception results (Table 7) also support the quantitative findings. Around 81% of faculty agreed that OBE improves learning quality and 80% reported increased student engagement. However, a high percentage of faculty (83%) also indicated the need for additional training. This shows that while OBE is effective, its implementation requires continuous academic support and faculty development.

The regression analysis provides further analytical validation of the results. The model explains 64.7% of the variance in student learning outcomes ($R^2 = 0.647$), which indicates a strong predictive relationship. OBE implementation level emerged as the strongest predictor ($\beta = 0.425$), followed by faculty training quality and assessment innovation. This suggests that successful OBE outcomes depend not only on curriculum structure but also on institutional and pedagogical factors.

Employment outcome comparison (Table 9) presents one of the most significant findings of the study. Placement rates increased from 64.8% to 83.2%, and the average starting salary rose from ₹3.72 lakhs to ₹4.58 lakhs. The reduction in time to employment from 4.5 months to 2.9 months further indicates improved job readiness among OBE-trained graduates. These results show strong alignment between academic outcomes and industry expectations.

Industry feedback also confirms the relevance of OBE in professional education. Higher employer satisfaction scores and preference for skill-oriented graduates suggest that outcome-based learning helps in reducing the gap between academic training and workplace competency requirements.

At the same time, the study also identified implementation challenges. Table 10 shows that faculty training requirements (mean = 4.31) and resource constraints (mean = 4.18) were the most severe challenges. This indicates that OBE effectiveness is closely linked with institutional support and infrastructure availability.

Overall, the discussion of quantitative and

qualitative findings suggests that OBE has a positive and statistically significant impact on accounting education. It improves conceptual clarity, practical learning, employability skills, and industry readiness. However, the results also highlight that effective implementation requires systematic faculty training, proper assessment design, and strong institutional commitment under the framework of NEP 2020.

Practical Implications and Policy Recommendations

The findings of this study have some clear practical meaning for accounting education. The results show that Outcome-Based Education is useful, but only when it is properly implemented in teaching and assessment. Just writing outcomes in documents is not enough. Actual classroom practices must also change.

One important implication is related to curriculum design. The study results showed improvement in practical application and analytical skills after OBE implementation. This means accounting courses should not remain only theory-focused. Subjects like Financial Accounting, Auditing, and Management Accounting should include more applied tasks, case work, and problem-based learning.

Faculty training is another major implication. The data and faculty responses in the study clearly indicate that teachers need training to implement OBE effectively. Many faculty members accepted that outcome-based teaching requires more planning and effort. Without proper training, the expected learning outcomes may not be fully achieved. Therefore, institutions should conduct regular workshops and training programs for faculty.

Assessment practices also need gradual change. Traditional exams mainly test memory and theoretical knowledge. However, the study findings showed better learning when activity-based and performance-based evaluation methods were used. Presentations, assignments, and practical projects can help in measuring real competencies in accounting education.

The study also highlights the importance of industry linkage. Employment outcome data and employer feedback suggest that skill-oriented graduates are more preferred. This indicates that accounting programs should include internships, industry interaction, and real-world exposure. Such steps can reduce the gap between academic learning and

professional requirements.

From a policy point of view, the findings support the direction of NEP 2020, which focuses on competency-based education. However, policy implementation at the institutional level is equally important. Institutions with better planning and academic support showed smoother adoption of OBE practices during the study.

Resource and infrastructure support also play a practical role. Some institutions faced challenges related to workload, training, and academic planning. This shows that OBE should be implemented gradually rather than suddenly. A phased approach may be more realistic and sustainable.

Overall, the study suggests that OBE can improve accounting education in terms of understanding, practical learning, and skill development. At the same time, continuous faculty support, curriculum alignment, and institutional commitment are necessary for effective implementation under NEP 2020.

Limitations

his study, while comprehensive in scope, is subject to several limitations that must be acknowledged.

- 1. Geographical and Institutional Scope:** The sample was limited to eight institutions across three Indian states. Although these were chosen for diversity and OBE activity, findings may not fully represent the heterogeneity of accounting education nationwide.
- 2. Time Horizon:** The study employed a cross-sectional design with a six-month follow-up, which restricts the ability to assess long-term career progression, retention of competencies, and professional certification performance over time.
- 3. Implementation Variability:** Differences in institutional culture, resource availability, and faculty expertise may have influenced OBE outcomes, making it difficult to isolate the effects of OBE practices from contextual factors.
- 4. Self-reported Measures:** While multiple data sources were triangulated, some employability indicators relied on student self-assessment, which may introduce response bias.

These limitations open several promising directions for future research. Longitudinal studies should

track OBE-trained graduates over multiple years to evaluate sustained professional growth, job mobility, and contributions to organizational performance. Comparative studies across disciplines, regions, and institutional types can further clarify the conditions under which OBE yields optimal results. Additionally, intervention-based research exploring the impact of specific implementation strategies — such as faculty development models, technology-enabled simulations, or industry-embedded capstone projects — would provide actionable evidence to refine OBE practice. Finally, cross-cultural comparative analyses can situate India's OBE trajectory within the broader global discourse, identifying both transferable lessons and locally unique dynamics.

Conclusions

This study was conducted to examine the impact of Outcome-Based Education (OBE) on accounting education in the context of NEP 2020. The overall results show that OBE has a positive effect on student learning and skill development. The improvement was visible in understanding, practical performance, and classroom engagement.

The findings indicate that students performed better after the implementation of OBE. There was clear improvement in conceptual clarity and application-based learning. This is important because accounting education requires logical thinking and practical understanding, not only memorization. Students appeared more confident while solving applied and problem-based questions.

The study also shows gradual improvement in analytical skills and employability-related competencies. Skills such as problem-solving, teamwork, and adaptability improved after outcome-based teaching practices were used. This suggests that structured learning outcomes and activity-based teaching support deeper learning in accounting education.

Faculty responses also support the results of the study. Most teachers observed higher student participation and better engagement in class. At the same time, they also reported challenges such as additional workload and the need for proper training. This indicates that effective implementation of OBE depends on faculty preparedness and institutional support.

Another important observation is related to employment outcomes. The study findings suggest better job readiness among students trained under

OBE. Improved placement rates and reduced time to employment indicate stronger alignment between academic learning and industry expectations.

However, the study also has certain limitations. The research was conducted in selected institutions and within a limited time period. Differences in infrastructure, faculty readiness, and academic environment may influence the results. Therefore, the findings should be interpreted carefully and may vary in different institutional settings.

Overall, the study concludes that OBE is a useful approach for improving the quality of accounting education under NEP 2020. It supports conceptual understanding, practical learning, and skill development. However, its long-term success depends on proper implementation, continuous faculty training, and consistent institutional effort rather than only policy-level adoption.

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Forensic Accounting as an Emerging Discipline: A Student Perspective from Mumbai City

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Citation: Subhadra, G.V. (2026). Forensic Accounting as an Emerging Discipline: A Student Perspective from Mumbai City. *Indian Journal of Accounting*, 58(1), 25-32

ABSTRACT

To combat financial fraud, forensic accounting has emerged as an important tool. This study attempts to examine the awareness of students in Mumbai city with reference to its perceived benefits and effective pedagogical approaches. The research design was descriptive in nature. A survey of 106 students studying in graduation and post-graduation in Mumbai city was conducted using convenience sampling. The findings of the study indicate that forensic accounting is perceived as an emerging and distinct field but understood inadequately by students in Mumbai city. The students didn't see professional advantages of forensic accounting education clearly with reference to employability, fraud examination, or expert witnessing due to their lack of industry exposure, limited awareness, and knowledge of forensic accounting. With reference to teaching methods for learning forensic accounting, the students found cases studies, research papers, textbooks, and guest speakers moderately effective. Video as a teaching mechanism was not preferred by students. Female respondents showed higher mean ranks (relative high agreement) in comparison to male respondents with reference to forensic accounting differs from traditional auditing. Furthermore, female respondents had a strong preference towards case study as a learning mechanism. Benefits with reference to forensic accounting were perceived similarly between male and female respondents..

Keywords

Forensic Accounting, Student Awareness, Perceived Benefits, Teaching Learning Mechanisms

Introduction

The need and importance for forensic accounting have been demonstrated through rising incidence of financial frauds. Forensic accounting has been recognized as a specialized discipline within the broader accounting profession. It detects, prevents, and investigates financial irregularities through investigative, analytical, and legal expertise. Developed economies are adopting sophisticated tools of forensic accounting while emerging economies are still in early stages of implementation. Understanding how forensic accounting will be perceived by students with reference to its benefits and effective teaching learning mechanism is essential for advancing the field of forensic accounting academically and professionally. Hence, this study attempts to

examine the awareness of students in Mumbai city with reference to its perceived benefits and effective pedagogical approaches.

Research Objectives

1. To evaluate the awareness and perceptions of students regarding the scope of forensic accounting.
2. To assess the perceived benefits of forensic accounting education among students
3. To identify and evaluate the effectiveness of different learning mechanisms in the teaching of forensic accounting courses among students
4. To find out the perception of gender towards awareness of forensic accounting, its benefits, and teaching mechanisms to learn forensic accounting

Literature Review

Gurpreet Kaur (2024) in the study titled, "Forensic Accounting: A Tool for Fraud Prevention and Detection," mentioned that forensic accounting is getting attention recently due to the rise in financial scandals and fraudulent activities. The researcher showed significant impact of forensic accounting for uncovering instances of financial fraud. The researcher is of the opinion that undergraduate students should be educated in the field of forensic accounting. The researcher further mentions for training of corporate staff members in the field of forensic accounting. The researcher concluded by mentioning that legal framework should be enhanced so that forensic accounting strategies gets promoted in India.

Parveezulla et al. (2024) in the study titled, "Unveiling Forensic Accounting: Practitioner Insights into Awareness and Effectiveness in Fraud Prevention," mentioned that forensic accounting is essential in today's society due to high fraud rates. However, practitioners adopt a diverse forensic accounting methodologies in India. The finding indicated that practitioners were familiar with forensic accounting as they reported average score of 3.87 on a five-point scale with reference to their awareness. However, the researchers reported challenges in implementation of forensic accounting such as high cost, restricted resource provision, and lack of training. The researchers concluded by mentioning that training sessions and seminars should be organized for practitioners for enhancing fraud prevention.

Ronak Gupta et al. (2024) in the study titled, "The Role of Forensic Accounting in Fraud Detection," mentioned that financial fraud is a critical issue among various industries and forensic accounting will detect and prevent it. The common fraud types include manipulation of financial statements, healthcare billing fraud, and embezzlement. To detect fraud, the researchers mentioned to use forensic auditing. The researchers mentioned that limited data access, high investigation costs, and time constraints are the major challenges of using forensic accounting techniques. The researchers found that digital forensics and data analytics can help in enhancing fraud detection. The researchers concluded by mentioning that machine learning and AI should be integrated into forensic accounting for better fraud detection and prevention.

K. Sanskriti (2023) in the study titled, "A Study on Awareness of Forensic Accounting with

Reference to Hyderabad City," mentioned that forensic accounting plays an important role to uncover financial crimes. Forensic accountants play an important role with client analysis and investigations. The field of forensic accounting even looks into personal financial disputes. The researchers in the study found that undergraduate students in Hyderabad city lack awareness regarding forensic accounting. The researcher is of the opinion that awareness campaigns should be conducted using social media platforms. The researcher concluded by mentioning that demand for forensic accountants are likely to increase which will enhance the integrity of financial system.

Ogunode Olubunmi A. and Dada Samueol O (2022) in the study titled, "Fraud Prevention Strategies: An Integrative Approach on the Role of Forensic Accounting," mentioned that forensic accounting combats fraud not only at corporate level but also at national level. The researchers found that in developed countries, there has been an appreciable use of forensic accounting tools and techniques. However, with reference to emerging economies, it is still in embryonic stage. The researchers cite lack of political will, poor ethical goals set by management, and lack of skilled forensic accountants. The researchers are of the opinion to upskill anti-fraud professionals by training them on latest anti-fraud technologies.

Based on the literature, no study has been carried out in Mumbai City which attempts to examine the awareness of students in Mumbai city with reference to perceived benefits and effective pedagogical approaches to Forensic Accounting.

Research Methodology

The researchers used a descriptive research design and convenience sampling to collect data from 106 graduate and post graduate students in Mumbai city. The questionnaire consisted of demographic questions and Likert Scale questions. Students were interviewed using a questionnaire. The interviews were held in the month of August and September 2025. The researchers used SPSS to check normality of data and testing of hypothesis. Furthermore, excel was used by the researchers to calculate effect size using Rank-Biserial Correlation.

Data Analysis

The demographic profile of respondents were students studying in graduation and post-graduation in Mumbai city. A total of 106 students were surveyed with 58 female students and 48 male students. The normality of data was tested using

Table 1 Testing of Normality

Statements	Normal Parameters ^{a,b}		Most Extreme Differences			Test Statistic	Asymp. Sig. (2-tailed)
	Mean	Std. Deviation	Absolute	Positive	Negative		
How much knowledge do you have about forensic accounting?	2.80	1.055	0.244	0.209	-0.244	0.244	.000 ^c
Forensic accounting is a relatively new area of accounting	3.66	0.872	0.255	0.197	-0.255	0.255	.000 ^c
The forensic accounting is different from traditional auditing	3.76	0.823	0.229	0.229	-0.207	0.229	.000 ^c
Forensic Accounting education strengthens the credibility of financial reporting	2.64	1.080	0.290	0.290	-0.191	0.290	.000 ^c
Forensic Accounting education makes students more desirable in the market place	2.93	1.089	0.210	0.210	-0.139	0.210	.000 ^c
Forensic Accounting education prepares students to engage in fraud examination	3.08	1.136	0.206	0.206	-0.162	0.206	.000 ^c
Forensic Accounting education prepares students to engage in expert witnessing	3.12	1.152	0.203	0.203	-0.118	0.203	.000 ^c
Use of Case studies as an effective Learning Mechanism for forensic accounting	3.24	1.143	0.192	0.138	-0.192	0.192	.000 ^c
Use of Videos as an effective Learning Mechanism for forensic accounting	2.90	1.014	0.214	0.214	-0.182	0.214	.000 ^c
Use of Research paper as an effective Learning Mechanism for forensic accounting	3.46	1.156	0.189	0.146	-0.189	0.189	.000 ^c
Use of Textbook as an effective Learning Mechanism for Forensic Accounting	3.38	1.099	0.233	0.144	-0.233	0.233	.000 ^c

Use of Guest speaker as an effective Learning Mechanism for Forensic Accounting	3.45	1.180	0.197	0.131	-0.197	0.197	.000 ^c
a. Test distribution is Normal.							
b. Calculated from data.							
c. Lilliefors Significance Correction.							

Source: Primary Data

One Sample Kolmogorov-Smirnov Test. The results of the test are shown in Table 1 which indicated that the data was not normally distributed as the p-value was less than 0.05. Hence, One Sample

Wilcoxon Signed Rank test (non-parametric test) was used by the researchers.

As seen in Table 2, the researchers did not find significant differences across statements number

Table 2 Testing of Hypothesis

Sr. No.	Research Objective	Null Hypothesis	Test Statistic	Standard Error	Standardized Test Statistic	Asymptotic Sig. (2-sided test)	Decision
1	RO 1	The median of knowledge you have about forensic accounting equals 3	611	124.239	-1.968	0.049	Reject the Null Hypothesis
2	RO 1	The median of forensic accounting is a relatively new area of accounting equals 3	2336	168.388	6.069	0.000	Reject the Null Hypothesis
3	RO 1	The median of forensic accounting is different from traditional accounting equals 3	2186	153.325	6.829	0.000	Reject the Null Hypothesis
4	RO 2	The median of forensic accounting education strengthens the credibility of financial reporting equals 3	1084	203.003	-3.042	0.002	Reject the Null Hypothesis
5	RO 2	The median of forensic accounting education makes students more desirable in market place equals 3	1306	174.635	-0.467	0.641	Retain the Null Hypothesis
6	RO 2	The median of forensic accounting education makes students to engage in fraud examination equals 3	1267.5	153.625	0.836	0.403	Retain the Null Hypothesis

7	RO 2	The median of forensic accounting education makes students to engage in expert witnessing equals 3	1548	170.446	1.373	0.17	Retain the Null Hypothesis
8	RO 3	The median of effectiveness of Case Study as a Learning Mechanism equals 3	1740	177.315	1.988	0.047	Reject the Null Hypothesis
9	RO 3	The median of effectiveness of Videos as a Learning Mechanism equals 3	906	140.855	-0.951	0.341	Retain the Null Hypothesis
10	RO 3	The median of effectiveness of Research Paper as a Learning Mechanism equals 3	2170	186.11	3.799	0.000	Reject the Null Hypothesis
11	RO 3	The median of effectiveness of Textbook as a Learning Mechanism equals 3	2215	193.943	3.274	0.001	Reject the Null Hypothesis
12	RO 3	The median of effectiveness of Guest Speaker as a Learning Mechanism equals 3	2244.5	193.507	3.638	0.000	Reject the Null Hypothesis

Source: Primary Data

5,6, and, 7 related to research objective 2 and statement number 9 related to research objective 3. In all these cases, the researchers retained the null

hypothesis as p-value was greater than 0.05. For all remaining statements, the researchers rejected the null hypothesis as the p-value was less than 0.05.

Table 3 Rank-Biserial Correlation

Research Objective	Null Hypothesis	Rank-Biserial Correlation	Effect Size	Interpretation
RO 1	The median of knowledge you have about forensic accounting equals 3	-0.19	Small	Respondents reported to have limited and below average knowledge regarding awareness of forensic accounting.
RO 1	The median of forensic accounting is a relatively new area of accounting equals 3	0.59	Large	Respondents perceived strongly that forensic accounting is a relatively new domain within the accounting discipline

RO 1	The median of forensic accounting is different from traditional accounting equals 3	0.66	Large	Respondents perceived strongly that forensic accounting is distinct from traditional accounting.
RO 2	The median of forensic accounting education strengthens the credibility of financial reporting equals 3	-0.30	Moderate	Forensic accounting was perceived to reduce the credibility of financial reporting. This negative perception was likely influenced by below average awareness of forensic accounting.
RO 2	The median of forensic accounting education makes students more desirable in market place equals 3	-0.05	Negligible	Respondents perceived with no significant difference that forensic accounting education will improve student's market desirability due to their below average awareness of forensic accounting
RO 2	The median of forensic accounting education makes students to engage in fraud examination equals 3	0.08	Negligible	Respondents perceived with no significant difference that forensic accounting education prepares students for fraud examination due to their below average awareness of forensic accounting
RO 2	The median of forensic accounting education makes students to engage in expert witnessing equals 3	0.13	Small	Respondents perceived with no significant difference that forensic accounting education makes students to engage in expert witnessing due to their below average awareness of forensic accounting
RO 3	The median of effectiveness of Case Study as a Learning Mechanism equals 3	0.19	Small	Respondents perceived case study to be more effective in comparison to the neutral baseline. This indicated that even though students had below average awareness of forensic accounting they still recognize that case study learning has practical utility.
RO 3	The median of effectiveness of Videos as a Learning Mechanism equals 3	-0.09	Negligible	Respondents reported with no significant difference regarding watching videos related to forensic accounting as an effective learning mechanism.
RO 3	The median of effectiveness of Research Paper as a Learning Mechanism equals 3	0.37	Moderate	Respondents perceived research paper to be moderately effective learning mechanism. This indicated that even though students had below average awareness of forensic accounting they still value academic rigor and structured inquiry provided by research paper-based learning

RO 3	The median of effectiveness of Textbook as a Learning Mechanism equals 3	0.32	Moderate	Respondents perceived textbooks to be moderately effective learning mechanism. This indicated that even though students had below average awareness of forensic accounting they still value structured and comprehensive sources of information
RO 3	The median of effectiveness of Guest Speaker as a Learning Mechanism equals 3	0.35	Moderate	Respondents perceived guest speakers to be moderately effective learning mechanism. This indicated that even though students had below average awareness of forensic accounting they still acknowledge that practitioners led interactions can enrich their learning

Source: Primary Data

Rank-Biserial correlation as seen in Table 3 was used by the researchers to check if observed median was greater than hypothesized median. For calculating Rank-Biserial correlation standardized test statistic from Table 2 was divided by square root of N (N=106 and its square root is 10.296).

The researcher further tested the below hypothesis as follows using Mann-Whitney U Test.

H0: There is no significant difference regarding awareness of forensic accounting, benefits of forensic accounting, and mechanism to learn forensic accounting among gender.

H1: There is no significant difference regarding

awareness of forensic accounting, benefits of forensic accounting, and mechanism to learn forensic accounting among gender.

There was no significant difference among gender with reference to benefits of forensic accounting. However specific areas such as forensic accounting differs from traditional auditing showed significant differences as p-value was less than 0.05. Female respondents showed higher mean ranks (relative higher agreement) in comparison to male respondents. Furthermore, female respondents had a strong preference towards case study as a learning mechanism with p-value less than 0.05.

Table 4 Testing of Hypothesis for Gender Differences

Type	Statements	Gender	Mean Rank	Sum of Ranks	Mann-Whitney U	Asymp. Sig. (2-tailed)
Awareness of Forensic Accounting	How much knowledge do you have about forensic accounting?	Male	51.72	2482.50	1306.50	0.57
		Female	54.97	3188.50		
	Forensic accounting is a relatively new area of accounting	Male	49.13	2358.00	1182.00	0.15
		Female	57.12	3313.00		
	The forensic accounting is different from traditional auditing	Male	46.24	2219.50	1043.50	0.02
		Female	59.51	3451.50		
Benefits of Forensic Accounting	Strengthen the credibility of financial reporting	Male	50.34	2416.50	1240.50	0.30
		Female	56.11	3254.50		
	Make students more desirable in the market place	Male	47.89	2298.50	1122.50	0.07
		Female	58.15	3372.50		
	Prepare students to engage in fraud examination	Male	51.00	2448.00	1272.00	0.43
		Female	55.57	3223.00		
	Prepare students to engage in expert witnessing	Male	52.64	2526.50	1350.50	0.78
		Female	54.22	3144.50		

Mechanism to learn Forensic Accounting	Case studies	Male	47.07	2259.50	1083.50	0.04
		Female	58.82	3411.50		
	Videos	Male	50.66	2431.50	1255.50	0.36
		Female	55.85	3239.50		
	Research paper	Male	52.42	2516.00	1340.00	0.73
		Female	54.40	3155.00		
	Textbook	Male	54.01	2592.50	1367.50	0.87
		Female	53.08	3078.50		
	Guest speaker	Male	52.92	2540.00	1364.00	0.85
		Female	53.98	3131.00		

Source: Primary Data

Summary and Conclusion

The study found that forensic accounting is perceived as an emerging and distinct field but understood inadequately by students in Mumbai city. The students perceived that forensic accounting was perceived to reduce the credibility of financial reporting, mainly, due to limited awareness and knowledge of forensic accounting. The students didn't see professional advantages of forensic accounting education clearly with reference to employability, fraud examination, or expert witnessing due to their lack of industry exposure, limited awareness, and knowledge of forensic accounting. With reference to teaching methods for learning forensic accounting, the students found cases studies, research papers, textbooks, and guest speakers moderately effective. Video as a teaching mechanism was not preferred by students indicating preference for more interactive and academically rigorous methods in comparison to only passive learning. Overall, students acknowledged forensic accounting as new and different but lacked sufficient awareness to recognize its professional benefits. Female respondents showed higher mean ranks (relative high agreement) in comparison to male respondents with reference to forensic accounting differs from traditional auditing. Furthermore, female respondents had a strong preference towards case study as a learning mechanism.

Recommendations

Higher education institutions should integrate forensic accounting as a subject in commerce and management programs. For educating students regarding professional benefits of forensic accounting, seminars, awareness campaigns, and workshops should be organized for students. For providing internships, guest lectures, and case study-based learning, there should be collaboration between industry, professional bodies, and

academia.

Limitations of Study and Further Research

The sample size of 106 respondent was small compared to the size of population. The study was only conducted in Mumbai city and excludes perspectives from faculty and practitioners. The study can be extended beyond Mumbai city for knowing the perception of students towards awareness, benefits, effective teaching mechanisms related to forensic accounting.

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Effectiveness of Budgetary Control Over Operating Costs : ‘A Case Study of Tata Steel’

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Citation: Singh, H.O. (2026). Effectiveness of Budgetary Control over Operating Costs ‘A Case Study Of Tata Steel’. *Indian Journal of Accounting*, 58(1), 33-40

ABSTRACT

Budgetary control is a widely used managerial tool for planning, monitoring, and controlling costs in manufacturing organisations. However, in capital-intensive industries such as steel manufacturing, the effectiveness of budgetary control is often challenged by high operating leverage, volatile input prices, and limited short-term cost controllability. This study examines the effectiveness of budgetary control over operating costs using Tata Steel as a case study.

The study adopts a case-based applied research approach and relies on secondary data obtained from Tata Steel's published financial statements. Budgeted operating costs prepared using an incremental budgeting approach are compared with actual operating costs to identify and analyse cost variances. Cost-head-wise variance analysis is conducted to evaluate controllability and managerial effectiveness.

The findings reveal that Tata Steel achieved a net favourable variance in total operating cost, primarily driven by effective control over raw material costs and manufacturing overheads. However, certain cost components such as employee costs and selling and distribution expenses exhibited adverse variances, reflecting their limited short-term controllability and sensitivity to market conditions. The study concludes that while budgetary control remains an effective tool at an aggregate level, its effectiveness varies across cost categories depending on cost behaviour and external influences. The paper highlights the importance of flexible budgeting practices and MIS-based monitoring systems to enhance operating cost control in large manufacturing firms.

Keywords

Budgetary Control, Cost Variance Analysis, Operating Costs, Manufacturing Industry, Management Accounting, Tata Steel.

Introduction

Background of the Study

In large manufacturing organisations, effective cost management is critical for sustaining profitability and operational efficiency. Capital-intensive industries such as steel manufacturing are characterised by high operating leverage, volatile input prices, and energy-intensive production processes. Under such conditions, even small inefficiencies in operating cost control can significantly affect financial performance.

Budgetary control is a key managerial tool used to plan, monitor, and regulate operating costs. It involves setting cost benchmarks through budgets,

comparing actual performance with these benchmarks, analysing variances, and taking corrective actions. While budgeting systems are widely implemented in large organisations, the persistence of cost variances raises concerns about their practical effectiveness.

This study examines the effectiveness of budgetary control over operating costs using Tata Steel as a case study.

Concept of Budgetary Control

Budgetary control is a systematic process of preparing budgets, comparing actual results with budgeted figures, and analysing deviations to ensure that organisational objectives are achieved

efficiently. In manufacturing firms, budgets are prepared for major operating cost components such as raw materials, employee costs, manufacturing overheads, administrative expenses, and selling and distribution costs.

The effectiveness of budgetary control depends on:

- Accuracy of forecasting
- Nature and controllability of costs
- Timeliness of monitoring
- Managerial response to variances

Importance of Operating Cost Control

Operating costs constitute a substantial portion of total expenditure in steel manufacturing. Unlike revenue, which is largely influenced by market forces, operating costs are relatively more controllable through managerial planning and operational efficiency. Effective control over operating costs helps organisations maintain margins, absorb external cost shocks, and improve competitiveness.

Company Profile (Brief)

Tata Steel Limited is one of India's leading integrated steel manufacturers, with operations spanning mining, production, and distribution. The company operates in a highly competitive and cyclical environment, making cost control a critical aspect of managerial decision-making.

Scope of the Study

The study focuses exclusively on **operating costs** and their control through budgetary mechanisms. Inventory-related elements such as opening and closing stock have been deliberately excluded to maintain analytical clarity and concentrate on operating cost controllability rather than working capital management.

Review of Literature

Budgetary control has long been recognised as a fundamental tool of management accounting for planning and controlling organisational activities. Horngren, Datar, and Rajan (2018) describe budgetary control as a mechanism that links strategic objectives with operational performance through cost planning and variance analysis. Their work emphasises the role of budgets in promoting coordination and accountability within organisations.

Drury (2015) highlights that the effectiveness of budgetary control depends significantly on the na-

ture of costs involved. According to the author, fixed and semi-fixed costs tend to exhibit predictable behaviour, whereas variable costs are more sensitive to operational volume and external factors. This distinction is particularly relevant in manufacturing industries with high operating leverage.

Atrill and McLaney (2019) argue that traditional budgeting techniques often face limitations in volatile business environments. Their study suggests that incremental budgeting, while simple and widely used, may not adequately capture sudden changes in input prices or market conditions. As a result, variance analysis becomes essential to identify inefficiencies and guide managerial action.

Studies focusing on manufacturing industries indicate that raw material and energy costs are among the most significant contributors to cost volatility. CIMA (2020) notes that external factors such as commodity price fluctuations and energy market instability reduce short-term cost controllability, thereby weakening the predictive power of static budgets.

Indian studies on cost management practices in large manufacturing firms emphasise the growing importance of management accounting tools in improving cost efficiency. ICAI (2021) observes that effective budgetary control, when supported by responsibility accounting and management information systems, enhances managerial decision-making and operational discipline.

While prior literature extensively discusses budgeting techniques and variance analysis, much of the research remains conceptual or industry-wide. There is relatively limited applied research that evaluates the practical effectiveness of budgetary control using real company-level operating cost data, particularly in the context of Indian steel manufacturing firms.

Research Gap

The review of existing literature indicates that although budgetary control and variance analysis have been widely studied, several gaps remain. First, much of the existing research is either theoretical in nature or focuses on broad industry-level trends, offering limited insight into firm-specific cost control effectiveness. Second, there is a lack of applied case-based studies that examine budgetary control using detailed operating cost variance data from large manufacturing organisations.

Moreover, limited attention has been given to analysing how different operating cost components respond to budgetary control mechanisms, particularly in capital-intensive industries characterised by high fixed costs and external cost volatility. In the Indian context, empirical studies focusing on operating cost controllability in steel manufacturing firms remain scarce.

This study seeks to bridge these gaps by conducting a case-based analysis of Tata Steel, focusing specifically on operating cost variances and their implications for budgetary control effectiveness. By using actual budgeted and actual cost data, the study contributes practical insights into how budgetary control functions in a real manufacturing environment and highlights areas where traditional budgeting approaches may require refinement.

Objectives of the Study

Objectives

The primary objective of this study is to evaluate the effectiveness of budgetary control in managing operating costs in a large manufacturing organisation. Budgetary control plays a crucial role in planning and monitoring costs; however, its effectiveness varies across cost components depending on their controllability and exposure to external factors.

Specifically, the study aims to analyse the differences between budgeted and actual operating costs of Tata Steel and to identify major cost variances across different operating cost heads. By examining these variances, the study seeks to assess how effectively budgetary control mechanisms function in practice.

Further, the study aims to evaluate the controllability of various operating cost components and to identify areas where traditional budgeting techniques may be insufficient. Based on the findings, the study proposes managerial measures to improve operating cost control and strengthen budgetary practices in large manufacturing firms.

Research Questions

- To what extent does budgetary control effectively manage operating costs in Tata Steel?
- Which operating cost components exhibit strong controllability under budgetary control?
- What managerial measures can enhance the effectiveness of budgetary control systems?

Research Methodology

Research Design

The study adopts a case-based applied research design, focusing on Tata Steel as a representative large manufacturing organisation. A case-based approach is appropriate as it allows an in-depth examination of budgetary control practices using real organisational data. The study is analytical in nature and aims to evaluate cost control effectiveness rather than establish causal relationships.

Nature and Sources of Data

The study relies entirely on **secondary data**, obtained from publicly available sources. The primary data source includes the published Annual Reports of Tata Steel, specifically the Statement of Profit and Loss and the accompanying Notes to Accounts. These sources provide reliable and audited financial information suitable for academic analysis.

No confidential or proprietary data has been used in the study. The use of secondary data ensures objectivity and replicability, which are essential characteristics of academic research.

Period of the Study

The analysis covers the **Financial Year 2024–25**. This period was selected to reflect the most recent operating cost structure and budgeting outcomes of the company at the time of study.

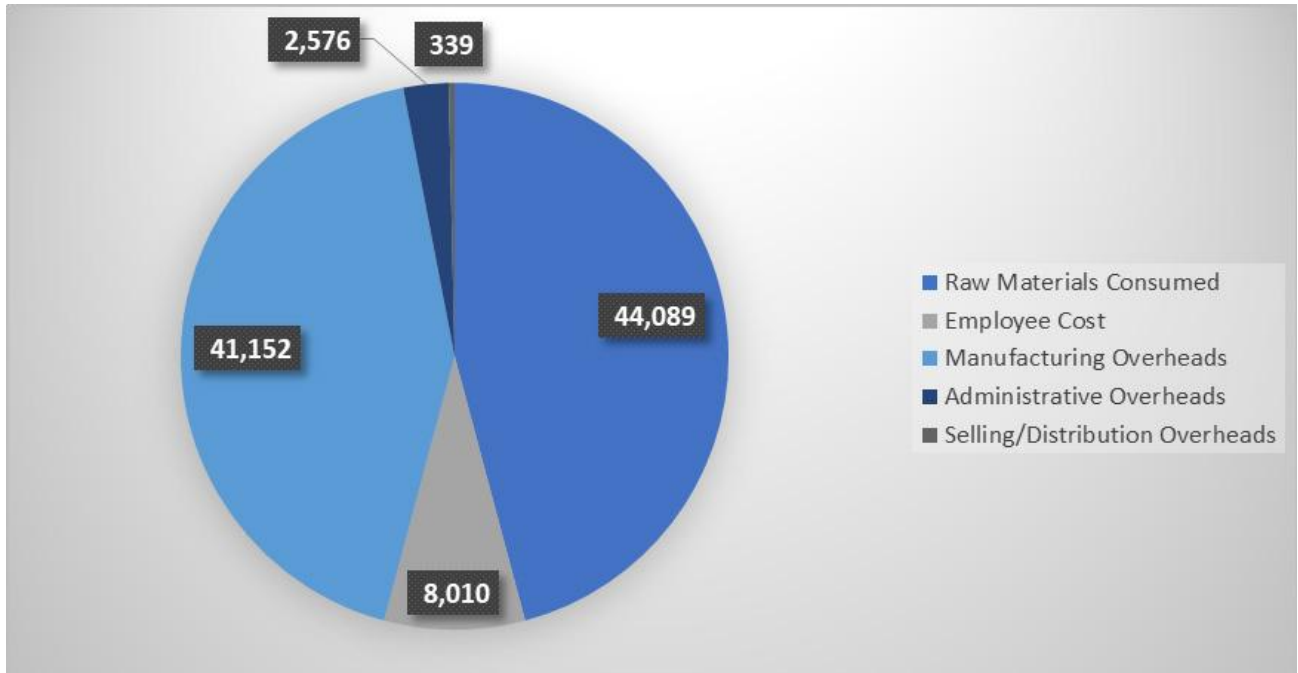
Budget Preparation Approach

An **incremental budgeting approach** was adopted for the preparation of budgeted operating costs. Under this approach, the actual operating costs of the previous financial year were used as a base and adjusted for expected changes such as inflation, price trends, and operational conditions. Incremental budgeting was selected as it reflects common budgeting practices followed by large manufacturing organisations.

Cost Classification and Scope

Expenses reported in the Statement of Profit and Loss were reclassified into cost accounting heads, including raw materials consumed, employee costs, manufacturing and plant overheads, administrative overheads, and selling and distribution expenses. The study focuses exclusively on **operating costs**, deliberately excluding inventory-related components to maintain analytical clarity and concentrate on cost controllability.

Figure 1: Actual Operating Cost Composition (₹ Crore)



Analytical Tools Used

The study employs comparative analysis of budgeted and actual costs, cost-head-wise variance analysis, and interpretation of favourable and adverse variances. In addition, an MIS dashboard has been used as a supporting analytical tool to visualise cost performance and enhance managerial interpretation.

Limitations of the Study

The study is subject to limitations such as reliance on secondary data, analysis restricted to a single financial year, and findings derived from a single-company case study. As a result, the findings may not be fully generalisable across industries or time periods.

Data Analysis and Interpretation

Overview of Operating Cost Structure

As shown in Figure 1, Operating costs at Tata Steel are dominated by raw material consumption, followed by manufacturing overheads, employee costs, and other operating expenses. This structure highlights the importance of controlling procurement, energy usage, and operational efficiency.

Budget vs Actual Operating Cost Comparison

As shown in Figure 2, the comparison between

budgeted and actual operating costs reveals variations across different cost heads, indicating areas of effective control as well as areas requiring managerial attention.

Cost Head-wise Variance Analysis

Raw Materials Consumed: Variance: ₹8,308 crore – Favourable

This favourable variance indicates effective control over material procurement and usage. It represents the single largest contributor to overall cost savings.

Employee Cost: Variance: ₹238 crore – Adverse

The adverse variance reflects higher employee-related expenses, likely due to wage revisions and benefit-related costs. These costs are relatively fixed and less controllable in the short run.

Manufacturing/Plant Overheads: Net Variance: ₹2,360 crore – Favourable

Although certain components such as depreciation, freight, and conversion charges showed adverse variances, these were more than offset by favourable variances in:

- Power and fuel
- Repairs and maintenance
- Stores and spares
- Mining premium and royalties

This indicates strong operational cost control.

Figure 2: Budget vs Actual by Cost Head (₹ Crore)

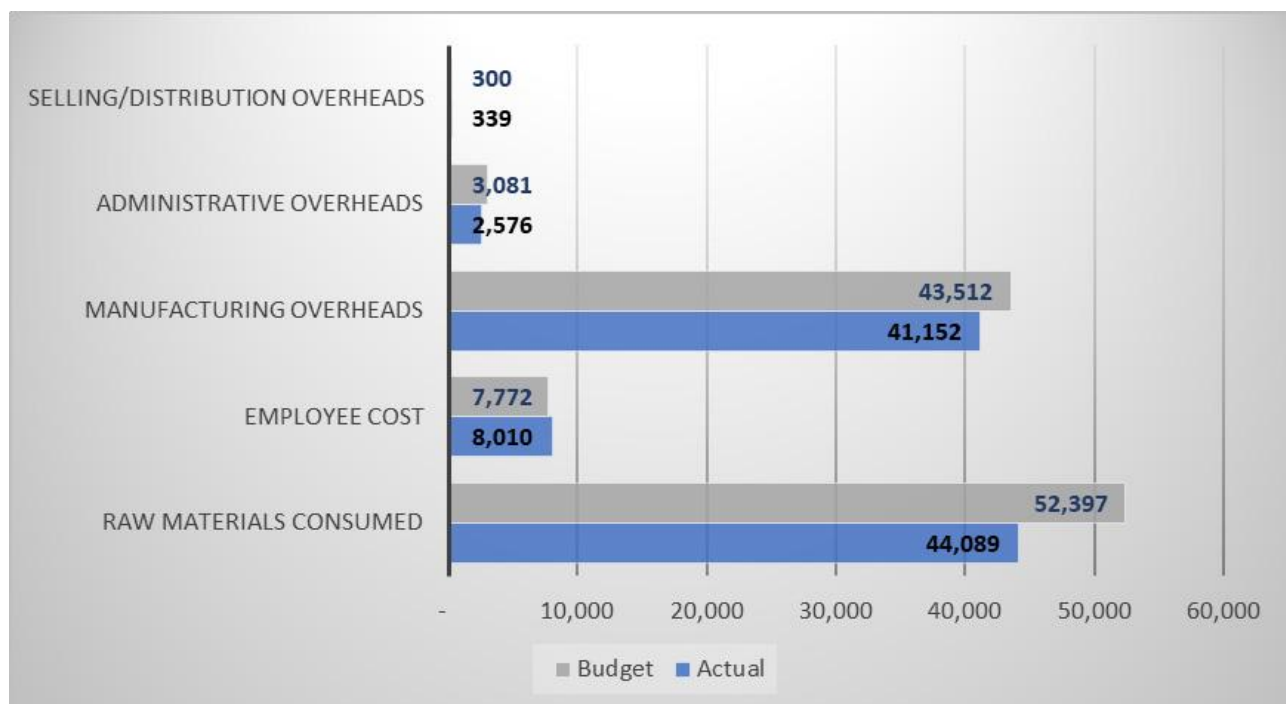
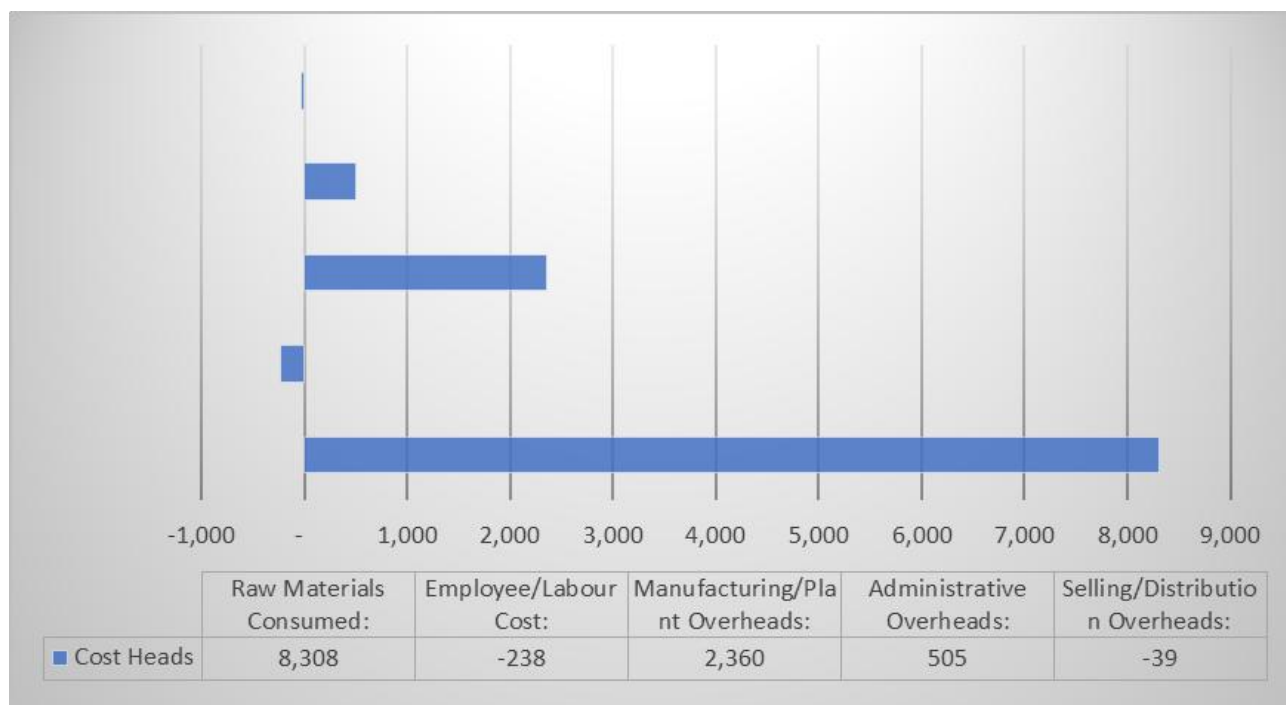


Figure 3: Variance – Favourable vs Adverse Cost Heads (₹ Crore)



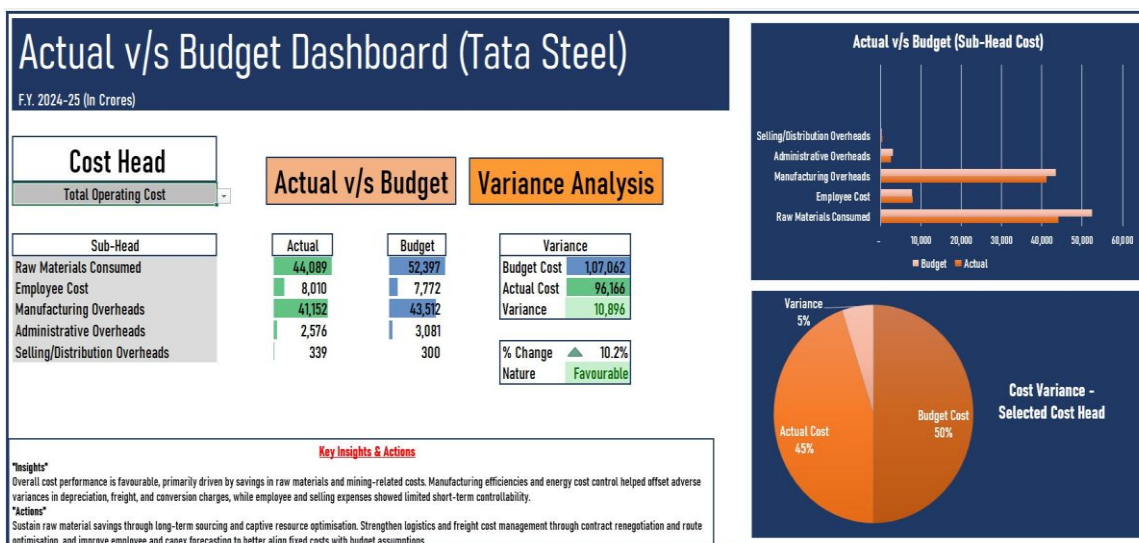
Administrative Overheads: Net Variance: ₹505 crore – Favourable

Savings in statutory charges and insurance costs outweighed adverse movement in rent and hire charges, reflecting effective administrative cost management.

Selling and Distribution Overheads: Variance: ₹39 crore – Adverse

As shown in Figure 3, the adverse variance is attributable to higher commissions and discounts, driven by market conditions and competitive pressures.

Figure 4: MIS Dashboard for Budgetary Control



Overall Operating Cost Performance

Total Operating Cost Variance: ₹10,896 crore – Favourable. Despite adverse variances in certain cost heads, Tata Steel achieved a net favourable variance in total operating cost, indicating effective overall cost control.

Role of MIS Dashboard in Budgetary Control

The MIS dashboard developed for this study provides a consolidated view of cost performance, enabling quick identification of variances and facilitating managerial decision-making.

Findings and Discussion

Key Findings

The analysis of budgeted and actual operating costs reveals that Tata Steel achieved a **net favourable variance in total operating costs**, indicating effective overall cost control during the period under study. This favourable outcome was primarily driven by strong control over raw material costs and manufacturing overheads, which together offset adverse variances in other cost heads.

The findings suggest that budgetary control mechanisms are effective at an aggregate level, although their effectiveness varies across individual cost components depending on their controllability and exposure to external factors.

Cost Heads with Strong Budgetary Control

The study finds that **raw material costs and manufacturing/plant overheads** exhibited strong budgetary control. The favourable

variance in raw material costs indicates effective procurement planning, operational efficiency, and disciplined material usage. Given the significance of raw materials in the cost structure of steel manufacturing, effective control in this area played a critical role in achieving overall cost savings.

Similarly, favourable variances in manufacturing overheads suggest improvements in operational efficiency, energy management, maintenance practices, and cost discipline at the plant level. These results indicate that internally managed operational costs are more amenable to budgetary control.

Cost Heads with Weak Budgetary Control

In contrast, **employee costs and selling and distribution expenses** displayed adverse variances, indicating relatively weaker budgetary control. Employee costs are largely fixed in the short run and influenced by wage revisions, contractual obligations, and workforce policies, limiting managerial flexibility.

Selling and distribution costs are influenced by market conditions, logistics costs, and competitive pressures. As a result, these cost heads exhibit lower short-term controllability, reducing the effectiveness of traditional budgeting approaches in managing deviations.

Fixed and Variable Cost Behaviour

The analysis highlights the importance of cost behaviour in understanding budgetary control effectiveness. Fixed and semi-fixed costs, such as employee and administrative expenses, demonstrate

relatively predictable behaviour but limited short-term controllability. Variable costs, including raw materials and certain overheads, are more sensitive to operational volume and external factors.

This distinction underscores the need for cost behaviour analysis as an integral component of budgeting and variance interpretation, particularly in capital-intensive industries.

Discussion of Results

The findings of the study align with management accounting literature, which suggests that traditional incremental budgeting techniques face limitations in volatile operating environments. While budgetary control remains an effective managerial tool, its effectiveness depends on the nature of cost components and the degree of managerial influence.

The results emphasise the need for flexible budgeting practices, continuous monitoring, and integration of digital tools such as MIS dashboards to enhance cost control effectiveness in large manufacturing organisations.

Managerial Implications and Recommendations

Given the significant contribution of **raw material costs** to overall operating expenses, management should strengthen procurement planning through long-term sourcing strategies, supplier diversification, and continuous monitoring of material usage. These measures can help mitigate price volatility and enhance cost predictability.

Effective management of **energy and power costs** is essential in steel manufacturing. Investments in energy-efficient technologies, optimisation of energy consumption, and adoption of alternative energy sources can improve cost control. Incorporating energy performance indicators into budgeting processes can further strengthen monitoring effectiveness.

The adverse variance in **employee costs** highlights the need for improved workforce planning and productivity monitoring. Linking budgetary control systems with performance management and incentive structures may enhance cost discipline while maintaining workforce motivation.

Departmental budgeting and responsibility accounting can strengthen control over **manufacturing and administrative overheads**. Clear

assignment of cost responsibility to cost centres enables management to identify inefficiencies and enforce budget discipline more effectively.

Selling and distribution costs are influenced by market conditions, logistics expenses, and competitive pressures, which limit their short-term controllability under traditional budgeting systems. The adverse variance observed in this cost head suggests that static budgets may not fully capture demand-driven fluctuations.

To improve cost discipline, management should adopt flexible budgeting and periodic review mechanisms. Monitoring logistics costs and commission structures can help reduce adverse deviations, even in the presence of external constraints.

Management Information Systems enhance budgetary control by improving the timeliness and transparency of cost information. MIS dashboards enable quick identification of cost variances and support timely managerial intervention.

The integration of digital tools with budgeting systems strengthens monitoring, accountability, and data-driven decision-making across cost centres.

Conclusion

This study examined the effectiveness of budgetary control over operating costs using Tata Steel as a case study. By comparing budgeted and actual operating costs and analysing cost-head-wise variances, the study assessed how effectively budgetary control mechanisms function in a large, capital-intensive manufacturing organisation.

The findings indicate that Tata Steel achieved a **net favourable variance in total operating costs**, demonstrating effective overall cost control during the period under study. Strong control over raw material costs and manufacturing overheads played a decisive role in offsetting adverse variances in employee costs and selling and distribution expenses. This highlights that budgetary control is more effective for cost components that are internally managed and operationally controllable.

The study also reveals that the effectiveness of budgetary control varies across cost categories depending on cost behaviour and exposure to external factors. Fixed and semi-fixed costs exhibit predictable patterns but limited short-term flexibility, while variable costs are more sensitive to

market and operational conditions. These findings reinforce the importance of cost behaviour analysis and continuous monitoring in budgetary control systems.

Overall, the study concludes that budgetary control remains a relevant and effective managerial tool for operating cost management. However, its effectiveness can be enhanced through flexible budgeting practices, integration of MIS-based monitoring systems, and a focused approach toward cost controllability rather than uniform cost reduction targets.

Limitations and Scope for Future Research

Limitations of the Study

While the study provides valuable insights into operating cost control, it is subject to certain limitations. The analysis is based on a **single-company case study**, which restricts the generalisability of findings across industries or firms. Additionally, the study covers **one financial year**, limiting the ability to assess long-term trends in budgetary control effectiveness.

Further, the study focuses exclusively on **operating costs** and deliberately excludes inventory and working capital components. As a result, the findings reflect operating cost controllability rather than overall financial performance or liquidity management.

Scope for Further Research

Future research can extend this study in several directions. A **multi-year analysis** may provide

deeper insights into the consistency and long-term effectiveness of budgetary control mechanisms. Comparative studies involving **multiple manufacturing firms or industries** could enhance the generalisability of results.

Further research may also incorporate **inventory and working capital management** to examine the interaction between cost control and liquidity. In addition, future studies can explore the effectiveness of **advanced budgeting techniques**, such as rolling budgets or zero-based budgeting, and the role of digital analytics in strengthening budgetary control systems.

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Digital Evolution in Indian Banking: Unveiling the Opportunities and Challenges of Payments Banks

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Citation: Kumari,P.S.,& Yadagiri.M.(2026). Digital Evolution in Indian Banking: Unveiling the Opportunities and Challenges of Payments Banks. *Indian Journal of Accounting*, 58(1),41-45

ABSTRACT

Payments Banks (PBs) have emerged as a major financial innovation in India with the primary objective of expanding financial inclusion. Established by the Reserve Bank of India (RBI), these specialized banks aim to deliver essential banking services such as deposits, remittances, and digital payment facilities to populations that have traditionally remained outside the formal banking system, including rural communities, migrant workers, and low-income groups. By relying largely on technology-driven and digital platforms, Payments Banks seek to bridge the gap between conventional banking services and financially underserved populations. In recent years, PBs have attracted considerable attention from researchers and policymakers, particularly regarding their role in promoting digital financial inclusion, addressing cybersecurity concerns, and adapting to evolving regulatory frameworks. Their distinct operational structure—characterized by restrictions on lending and limits on deposit acceptance—creates both opportunities and challenges for their growth and sustainability. On one hand, Payments Banks provide an efficient and low-cost mechanism for delivering last-mile financial services; on the other hand, their constrained revenue model raises questions about their long-term operational viability. In this context, the present study examines the opportunities and challenges faced by Payments Banks within India's financial ecosystem and explores the factors influencing their growth, operational sustainability, and competitive position in an increasingly digital financial environment. The study also emphasizes the importance of continued regulatory support, investment in advanced financial technologies, and the development of innovative customer-oriented financial products. Strengthening these aspects is essential not only for improving the performance of Payments Banks but also for ensuring their long-term sustainability and their contribution to building a more inclusive financial system in India..

Keywords

Challenges, Digital Banking, Digital India, Financial Inclusion, Fintech, Opportunities, Payments Banks.

Introduction:

Financial inclusion remains a key priority for India's economic progress. The Reserve Bank of India (RBI) created Payments Banks in 2014 as a specialized banking model to provide basic banking services to underserved segments of society. Payments Banks, unlike regular banks, have a limited scope, focusing on deposit-taking (up to ₹2 lakh per client), remittances, and digital transactions, but not giving credit services.

The introduction of digital payment technologies, as well as government-led financial inclusion efforts such as Jan Dhan Yojana and Digital India, have all contributed considerably to the rise of Payments Banks. By embracing mobile technology, these banks have enabled real-time transactions, reducing reliance on cash-based economies. Furthermore, their collaborations with FinTech companies and mobile network providers have improved accessibility even further, increasing the effectiveness and affordability of banking services.

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Payments banks still must deal with issues including cybersecurity threats, regulatory restrictions, and worries about their long-term viability. To ensure their long-term survival and contribution to India's digital financial ecosystem, it would be imperative to address these obstacles through legislative assistance and technology developments.

Review of Literature

The reviewed literature presents Payment Banks as a transformative force for promoting financial inclusion and digital banking in India. Janardhanudu and Srinivasa Rao [2025] highlight Payments Banks potential to reach rural and unbanked populations where traditional banks struggle, emphasizing mobile platforms as the most effective delivery medium. Saxena [2025] explores the evolution of digital payments post-demonetization, identifying demographic variables and behavioural factors such as trust, awareness, and digital literacy as central to the adoption of services like Paytm Payments Bank. Mamatha [2024] notes that Payment Banks saw increased adoption after demonetization, stressing the role of accessibility and technological ease in enhancing financial inclusion, while pointing out issues of profitability and customer engagement. Thomas [2024] discusses how trust, usability, and sustainable models affect the long-term success of Payment Banks, though their exact impact on financial inclusion remains inconclusive due to regulatory and market constraints. Sharma and Pareek [2023] emphasize Payments Banks focus on digital services and basic banking for rural populations, highlighting their influence on semi-urban financial behaviour despite limitations like low public awareness and technological challenges.

Thakkar [2022] discusses the role of Payments Banks in bridging financial disparities through affordability and simplicity but warns that weak promotion and low awareness hinder growth. Iyer [2021] assesses how Payments Banks support digital remittances and low-cost banking for low-income groups while being constrained by lack of credit services and regulatory bottlenecks. Bilange [2021] emphasizes that success depends on consumer trust, awareness, and the ability to compete with traditional banks and wallets.

Upadhyaya [2021] analyses operational models of different Payments Banks and highlights their varied approaches using postal networks and mobile platforms to extend services, albeit unevenly. Beevi

and Kalarani [2020] suggest the need for fintech innovation and outreach strategies to overcome limited-service offerings and market constraints. Yadav [2019] traces the origin of Payments Banks back to RBI's adoption of Nachiket Mor Committee recommendations, underscoring mobile-first models and the need to serve migrant workers and small businesses despite lacking credit facilities.

Das [2019] elaborates on FinTech and Payments Banks contribution to cost-efficient services, calling for stronger regulation and cyber risk oversight. Wadhwa and Agarwal [2019] explore barriers like behavioural resistance and infrastructure gaps, recommending awareness programs and fintech alliances. Elumalai and Panchalan [2019] study Payments Banks' low-cost services and RBI's ₹1 lakh deposit cap, identifying opportunities in remittances and limitations in revenue generation. Verma and Taluka [2018] view Payments Banks as both complement and competitor to traditional banks, citing secure investments and user acquisition as benefits, while revenue caps and rivalry remain issues.

Choudhury [2018] highlights the RBI's initiative to support underserved groups via mobile-first banking, stressing gaps in infrastructure and internet access. GSMA [2016] discusses agent-based models and capital costs, stressing the importance of adjacent revenue streams for sustainability. Business Today [2015] underscores the inspiration from M-Pesa, elaborating on the need for collaborations and mobile integration. The RBI's [2014] foundational framework highlights savings, transfers, and digital transactions for disadvantaged populations while outlining restrictions on lending and deposit limits to ensure safety and inclusion.

Together, these research studies provide a comprehensive view of Payments Banks contribution to financial inclusion in India. They reveal the structural, technological, and behavioural challenges while emphasizing the transformative potential of these institutions through mobile platforms, postal networks, and digital services. The literature indicates that sustained success will require regulatory reform, consumer trust-building, and inclusive technological infrastructure to overcome adoption barriers and support long-term viability.

Opportunities of Payments Banks in India

Improving Financial Inclusion

Payments Banks offer banking services to the un-

banked, particularly in rural areas, hence expanding financial inclusion. They also help marginalized groups gain access to crucial financial services by bridging the gap between traditional banking and the unbanked.

Digital Payment Revolution

With the growth of mobile banking and UPI, Payments Banks have enabled faster and more secure digital transactions. This revolution has improved payment mechanisms while also encouraging a cashless economy.

Financial Literacy and Awareness Programs.

Payments Banks can collaborate with government agencies and non-governmental organizations (NGOs) to undertake financial literacy programs that equip clients with the knowledge they need to make sound financial decisions. Such initiatives can boost digital banking adoption and build trust among new consumers.

Strategic Collaborations with E-Commerce Platforms

Payments Banks can increase their customer base by working with e-commerce and online marketplaces. This connection has the potential to increase transaction volumes while also improving client convenience.

Leveraging Big Data and Analytics

Payments Banks can employ big data analytics to understand client behaviour and personalize services accordingly. This data-driven strategy has the potential to result in the creation of innovative financial products as well as improved risk management.

Expansion of Micro savings and Investment Products

Payments Banks have the potential to create micro-savings programs and small-scale investment products geared toward low-income consumers. Diversifying their product offering can help them overcome revenue limits and reach a larger consumer base.

Cost-effectiveness via Advanced Technologies

Adoption of emerging technologies like as artificial intelligence, blockchain, and automation can help to cut operating costs while improving service delivery. These technical investments can help Payments Banks stay competitive in a fast-changing digital market.

Challenges of Payments Banks in India

Regulatory constraints

Payments banks are unable to offer credit services due to stringent rules, which limits their earning potential. These limits limit the product portfolio, making it difficult to compete with traditional banks.

Profitability Concerns

Payments banks struggle to establish long-term sustainability since they rely heavily on transaction fees. The limited income model, along with the inability to offer lending services, reduces total profitability.

Limited Product Portfolio Payments.

Banks provide a limited range of services, which may dissuade customers seeking comprehensive financial solutions. This narrow offering makes it difficult for businesses to diversify revenue streams and reach a larger audience.

Fierce competition from FinTech and Neobanks.

The increasing rise of FinTech firms and neobanks creates tremendous competition, requiring Payments Banks to innovate regularly. These competitors frequently provide a greater selection of digital financial services with superior user experiences.

Operational Scalability Issues

As digital adoption increases; payments banks have issues in extending their operational infrastructure. Maintaining constant service quality over an increasing network can tax existing systems and resources.

Customer Data Privacy and Consent

The reliance on digital platforms poses issues of data security and client privacy. Payments banks must manage stringent data privacy rules while keeping clients fully informed about data usage.

Dependence on Technological Infrastructure

Payments banks reliance on digital technology puts them exposed to technological mishaps and cyber threats. Maintaining a strong and resilient IT infrastructure is critical for avoiding service disruptions and protecting sensitive financial information.

Future Scope and Conclusion

Payments Banks hold immense potential to deepen financial inclusion through digital and mobile

platforms. Future developments should focus on regulatory reforms, allowing limited credit offerings and service diversification. Strategic collaborations with FinTech and e-commerce platforms can enhance reach and revenue. Investments in cybersecurity and data privacy will be crucial as digital reliance grows. Financial literacy programs must continue to build user trust and adoption. Leveraging technologies like AI and analytics can improve personalization and efficiency. Despite current limitations, Payments Banks can evolve into sustainable financial intermediaries. Their success depends on innovation, policy support, and customer-centric growth strategies.

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Impact of Artificial Intelligence Adoption on Accounting Education: An Empirical Study among Commerce Students in Higher Education Institutions

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Citation: Kumar, D. (2026). Impact of Artificial Intelligence Adoption on Accounting Education: An Empirical Study among Commerce Students in Higher Education Institutions. *Indian Journal of Accounting*, 58(1), 46-52

ABSTRACT

Artificial Intelligence (AI) is reshaping accounting education by influencing instructional practices, learning support, problem-solving, students' digital capabilities, and professional preparation. This study investigates the factors connected with Artificial Intelligence Adoption Intention (AIAI) among Commerce students in higher education that to with particular emphasis on accounting education. The study deployed a descriptive-analytical design and obtained primary responses from 261 Commerce students through a structured five-point Likert-scale instrument. The data were analysed by applying descriptive measures, reliability testing, exploratory component analysis, Pearson correlation, and multiple linear regression. The correlation results shown positive relationships between each explanatory construct and AIAI. In the regression model, AI Awareness level, Perceived Usefulness, Digital Competency, and Perceived Learning Benefits emerged as significant and positive predictors. Perceived Ease of Use was positively correlated to AIAI at the bivariate level but showed a negative coefficient when all predictors were applied simultaneously; this finding requires careful analysis and interpretation in the view of substantial multicollinearity. The model accounted for 83.9% of the variance in AIAI. The 24-item instrument depicts very high internal consistency (Cronbach's Alpha = 0.983), and the exploratory component analysis yielded three empirical components explaining 86.73% of the variance, with several cross-loadings. By adding AI Awareness, Digital Competency, and Perceived Learning Benefits to the Technology Acceptance Model, the study broadens its application to accounting education and offers implications for responsible and effective AI integration.

Keywords

Artificial Intelligence; Accounting Education; Artificial Intelligence Adoption Intention; Commerce Students; Digital Competency; Technology Acceptance Model.

Introduction

Artificial Intelligence is a major force influencing both accounting practice and higher education. Latest inventions including machine learning, robotic process automation, natural applied language processing, intelligent analytics, and generative AI are being applied to bookkeeping, auditing, fraud identification, financial reporting, forecasting, and decision support (Ballantine et al., 2024; Brabete et al., 2024). As these applications expand, accountants are moving beyond routine transaction processing towards analytical, advisory, and strategic roles. Consequently, accounting

graduates increasingly require a combination of disciplinary knowledge and digital capability.

Higher education institutions consequently have a central responsibility in equipping Commerce students for accounting work in AI-enabled environments. AI-supported educational applications can facilitate conceptual learning, problem resolution, feedback, personalised instruction, and digital literacy. Nevertheless, the educational value of such technologies depends substantially on students' readiness and interest to use them. Potential influences include AI Awareness, its Perceived Usefulness, and Perceived

Ease of Use, Digital Competency, as well as Perceived Learning Benefits.

Davis's (1989) Technology Acceptance Model (TAM) offers a well-established explanation of technology acceptance, particularly through Perceived Usefulness as well as its Perceived Ease of Use. Later extensions of the models introduced additional contextual and behavioural determinants (Venkatesh & Davis, 2000; Venkatesh et al., 2003; Venkatesh & Bala, 2008). In the present study, TAM is extended with AI Awareness, Digital Competency, and Perceived Learning Benefits to explain AIAI within accounting education.

Review of literature

The recent literature presents AI in education as both an opportunity and a source of new challenges. Ballantine et al. (2024) argued for the redesign of accounting education while retaining critical thinking and human judgement. Brabete et al. (2024) identified AI-related capabilities, digital skills, and analytical competence as increasingly important to accounting education. Ogunleye et al. (2024) stressed the need for institutional direction and responsible use of generative AI. Ghimire and Edwards (2024) showed that TAM constructs remain useful for understanding generative AI adoption in educational environments. Kayser and Telukdarie (2024) examined technology-acceptance considerations in accounting-related AI adoption, whereas Prabowo (2024) focused on technology readiness and digital competence among accounting students.

Within TAM, Perceived Usefulness as well as its Perceived Ease of Use are central explanatory factors in technology acceptance (Davis, 1989). A systematic synthesis by Yanfang et al. (2026) found that TAM, UTAUT, and ECM continue to offer useful perspectives on university students' adoption of AI. In the present context, greater AI Awareness may increase familiarity and reduce uncertainty; stronger Digital Competency may enable more effective interactions with AI applications; and recognition of educational benefits may encourage adoption. Together, these considerations provide a rationale for applying an extended TAM framework to AI use in accounting education.

Identified Research Gap

Despite the growing body of work on AI adoption, only a less empirical studies have focused specifically on accounting education from the

viewpoint of Commerce students, who represent a substantial pool of future accounting and business professionals. Much of the existing research has emphasised established technology-acceptance variables without simultaneously considering AI Awareness, Digital Competency, and Perceived Learning Benefits. Evidence relating to the Indian higher-education setting is also limited. The present study therefore evaluates the combined contribution of five determinants—AI Awareness, Perceived Usefulness, Perceived Ease of Use, Digital Competency, as well as its Perceived Learning Benefits—to AIAI among Commerce students.

Research objectives and hypotheses

The objectives are to depict the determinants of AIAI among Commerce students, evaluate their level of AI awareness, assess the perceived usefulness and its ease of AI use, examine the contributions of digital competence and learning benefits, and determine factors that may support AI integration in accounting education.

H1: AI Awareness is hypothesised to positively predict AIAI.

H2: Perceived Usefulness is hypothesised to positively predict AIAI.

H3: Perceived Ease of Use is hypothesised to positively predict AIAI.

H4: Digital Competency is hypothesised to positively predict AIAI.

H5: Perceived Learning Benefits are hypothesised to positively predict AIAI.

Research methodology

Descriptive-analytical design was deployed for the investigation. The study population consisted of undergraduate and postgraduate Commerce students enrolled in B.Com., B.Com. (Accounting and Finance), B.Com. (Corporate Secretaryship), and M.Com. programmes. Of the 275 questionnaires received, 261 complete responses were retained, producing an effective response of respondents are 94.91%.

Convenience sampling was deployed because eligible students were readily accessible through the participating higher education institutions and participation was voluntary. The approach was considered more satisfactory for the exploratory needs of the study and the practical limitations associated with access to respondents. Since the sample was non-probabilistic, the findings should not be generalised statistically to the

entire Commerce-student population and are best interpreted in relation to the sampled and similar settings.

The instrument comprised 24 measurement statements representing six constructs: AI Awareness (AA), Perceived Usefulness (PU), Digital Competency (DC), Perceived Ease of Use (PEOU), Perceived Learning Benefits (PLB), and AIAI. Items measuring PU as well as PEOU were taken from Davis (1989), while the DC construct was informed by Tzafilkou, Perifanou, and Economides (2022). Items for AA, PLB, and AIAI were developed and adapted to the study context from relevant literature on AI adoption, AI-

supported learning, and accounting education. The items were reviewed for and relevant to Commerce and accounting education and assessed using a five-point Likert scale. The corresponding source and adaptation details are presented in the table below.

The dataset was explored employed descriptive statistics, Cronbach's Alpha, exploratory component analysis, Pearson correlation, and multiple linear regression. These procedures were used respectively to evaluate the measurement instrument, describe the relationships with the constructs, and assess the proposed hypotheses. Respondents participated voluntarily; confidentiality and anonymity were maintained.

Construct	Source/Basis	Contextual Adaptation
AA	AI-literacy/AI-adoption literature	AI concepts, accounting applications, changes in professional practice, and recent developments
PU	Davis (1989), TAM	Perceived value for accounting learning, efficiency, problem solving, and academic performance
PEOU	Davis (1989), TAM	Ease, confidence, comprehension, and perceived user-friendliness of AI applications in accounting
DC	Tzafilkou et al. (2022), SDiCoS	Digital skills, adaptability, confidence, and independent use of AI
PLB	AI-supported learning/accounting education literature, including Ballantine et al. (2024)	Learning experience, conceptual understanding, feedback, and personalised learning
AIAI	AI-adoption literature, including Prabowo (2024)	Intention to use, continued use, future acceptance, and recommendation of AI in accounting education

5. RESULTS AND DISCUSSION

5.1 Sample Profile

Characteristic	Major distribution
Gender	Male 46.0%; Female 47.5%; Prefer not to disclose 6.5%
Age	Below 18: 13.8%; 18–20: 33.3%; 21–23: 32.6%; Above 23: 20.3%
Programme	B.Com 13.4%; B.Com A&F 26.4%; B.Com Corporate Secretaryship 13.8%; M.Com 25.7%; Other 20.7%
Institution	Government 19.5%; Aided 26.8%; Private/Self-financing 33.3%; University Department 20.3%
Previous AI use	Yes 79.3%; No 20.7%

Source: Computed from primary data.

Descriptive and Reliability Findings

Across the 24 measurement statements, the overall mean was 4.17 (SD = 0.86), reflecting a favourable overall perception of AI adoption. The construct mean for AI Awareness was 3.27, suggesting a moderate level of awareness. Perceived Usefulness also received positive evaluations, with the highest item mean of 3.58 relating to AI assistance in solving accounting problems. The 24-item scale produced a Cronbach's Alpha of 0.983, demonstrating excellent

internal consistency.

Measure	Result
Overall mean (24 items)	4.17
Overall SD	0.86
AI Awareness mean	3.27
Cronbach's Alpha	0.983
Number of items	24
Sample size	261

Source: Computed from primary data.

Pearson Correlation and Collinearity

Variable	AA	PU	PEOU	DC	PLB	AIAI
AA	1	.643	.902	.874	.765	.776
PU	.643	1	.675	.716	.775	.785
PEOU	.902	.675	1	.907	.778	.743
DC	.874	.716	.907	1	.827	.864
PLB	.765	.775	.778	.827	1	.827
AIAI	.776	.785	.743	.864	.827	1

Source: Computed from primary data.

Each of the five explanatory constructs was positively correlated with AIAI. Digital Competency recorded the highest correlation with AIAI ($r = 0.864$), followed by Perceived Learning Benefits ($r = 0.827$). On the contrary, the predictors were strongly interrelated, particularly PEOU with AA ($r = 0.902$) and DC ($r = 0.907$), suggesting considerable overlap among the explanatory variables.

The collinearity diagnostics revealed pronounced multicollinearity among the predictors. The VIF statistics were 49.258 for AA, 27.532 for PU, 82.964 for PEOU, 81.736 for DC, and 25.288 for PLB, while the respective tolerance values were 0.020, 0.036,

0.012, 0.012, and 0.040. These diagnostics indicate extensive shared difference among the predictors and therefore be careful when interpreting individual regression coefficients, particularly the negative coefficient associated with PEOU.

Multiple Regression Analysis

Statistic	Value
R	0.916
R ²	0.839
Adjusted R ²	0.836
Std. Error	0.533
F(5,255)	265.70, $p < 0.001$

Source: Computed from primary data.

The five-predictor regression equation accounted for 83.9% of the variability in AIAI and was statistically significant, $F(5,255) = 265.70$, $p < 0.001$.

Predictor	B	t	p	Decision
AA	0.266	3.905	<0.001	H1 Supported
PU	0.334	6.884	<0.001	H2 Supported
PEOU	-0.675	-6.353	<0.001	H3 Not supported in hypothesised positive direction
DC	0.819	9.976	<0.001	H4 Supported
PLB	0.204	3.934	<0.001	H5 Supported

Source: Computed from primary data.

The regression results identified AI Awareness, Perceived Usefulness, Digital Competency, and Perceived Learning Benefits as significant positive predictors of AIAI. Digital Competency recorded

the largest unstandardised coefficient ($B = 0.819$). Although PEOU was positively related to AIAI in the bivariate analysis, its coefficient became negative after simultaneous inclusion of the predictors. In

view of the very high intercorrelations and VIF values, this coefficient should not be interpreted as showing that ease of use independently reduces students' desire to adopt AI.

Exploratory Factor Analysis

An exploratory component analysis for the 24 measurement statements was done deploying Principal Component Analysis (PCA) with Varimax rotation. Sampling adequacy was high (KMO = 0.952), and Bartlett's test was statistically significant ($\chi^2 = 4587.364$, $df = 276$, $p < 0.001$), supporting the use of component analysis. Applying the eigenvalue-greater-than-one rule resulted in three retained components that jointly accounted for 86.73% of total variance. The rotated solution contained several substantive cross-loadings, indicating that the observed structure doesn't fit into the six constructs proposed theoretically. Accordingly, the EFA is interpreted as exploratory evidence rather than as conclusive confirmation of the six-construct measurement model.

Noticeable cross-loadings were observed for Q5, Q9, Q14, Q17, Q18, Q20, Q21, Q23, and Q24. These results point to overlap among several measurement

items and indicate that the empirical component structure does not reproduce the six proposed constructs cleanly. The factor analysis is therefore treated as an exploratory assessment rather than definitive construct validation.

Discussion of Findings

AI Awareness was a significant positive predictor of AIAI ($B = 0.266$, $p < 0.001$), in line with Prabowo (2024) and Yanfang et al. (2026), who emphasise the role of awareness and contextual familiarity in AI adoption. Perceived Usefulness also made a significant positive contribution ($B = 0.334$, $p < 0.001$), providing support for the TAM perspective and earlier technology-acceptance evidence (Davis, 1989; Venkatesh & Davis, 2000).

At the bivariate level, PEOU was strongly and positively associated with AIAI ($r = 0.743$). However, its regression coefficient became negative when the predictors were considered jointly ($B = -0.675$, $p < 0.001$). This departure from the conventional TAM expectation should be understood alongside the substantial multicollinearity in the predictor set and should not be taken to mean that ease of use independently suppresses AI adoption.

Item	Component 1	Component 2	Component 3
Q1	0.100	0.192	0.917
Q2	0.338	0.204	0.827
Q3	0.467	0.342	0.757
Q4	0.427	0.361	0.738
Q5	0.614	0.661	0.349
Q6	0.426	0.786	0.185
Q7	0.198	0.922	0.177
Q8	0.323	0.846	0.285
Q9	0.259	0.578	0.596
Q10	0.294	0.336	0.830
Q11	0.141	0.449	0.788
Q12	0.396	0.092	0.835
Q13	0.420	0.131	0.844
Q14	0.651	0.561	0.298
Q15	0.415	0.200	0.847
Q16	0.489	0.225	0.788
Q17	0.474	0.463	0.609
Q18	0.642	0.480	0.401
Q19	0.652	0.463	0.376
Q20	0.676	0.441	0.496
Q21	0.830	0.166	0.490
Q22	0.820	0.348	0.398
Q23	0.700	0.508	0.218
Q24	0.689	0.386	0.518

Source: Computed from primary data.

Digital Competency produced the strongest positive regression coefficient ($B = 0.819$, $p < 0.001$), supporting the importance of technological capability in AI-enabled accounting education and aligning with Brabete et al. (2024) and Prabowo (2024). Perceived Learning Benefits also had a significant positive coefficient ($B = 0.204$, $p < 0.001$), suggesting that students' recognition of educational value is relevant to their intention to adopt AI, consistent with Ballantine et al. (2024) and Brabete et al. (2024).

Findings, implications and conclusion

Major Findings

Overall, Commerce students expressed favourable views about AI adoption, although AI Awareness remained moderate (Mean = 3.27). Positive associations with AIAI for all five can be viewed as explanatory variables. In the simultaneous regression, AI Awareness, Perceived Usefulness, Digital Competency, and Perceived Learning Benefits were significant positive forecasters, whereas PEOU retained a positive bivariate relationship but showed a negative coefficient in the full model. The regression equation explained 83.9% of the variance in AIAI. The measurement scale showed excellent reliability ($\alpha = 0.983$), and the exploratory analysis yielded three empirical components accounting for 86.73% of variance, with several cross-loadings.

Practical, Theoretical and Policy Implications

From a theoretical perspective, the study broadens TAM through the inclusion of AI Awareness, Digital Competency, and Perceived Learning Benefits. From a practical viewpoint, higher education institutions can employ AI-enabled accounting applications in Commerce curricula, strengthen students' digital capabilities, create good opportunities for experiential learning, and provide faculty development on responsible AI use. Curriculum planners can integrate AI, data analytics, RPA, and business intelligence with accounting knowledge, critical reasoning, professional judgement, and ethics. At the policy and administrative levels, attention is required for digital infrastructure, faculty development, industry-academia links, academic integrity, data protection, transparency, and appropriate human oversight.

Directions for Further Research

Future studies could extend the evidence by comparing Commerce students with learners from other disciplines, conducting cross-national and cross-cultural investigations, and applying longitudinal designs. Additional determinants such as AI Trust in adopting AI, its Perceived Risk, Technology Anxiety, Institutional Support, Facilitating Conditions, AI Self-Efficacy, and Ethical Awareness could also be examined using larger probability-based samples. Because the present factor structure is exploratory, future research should employ CFA and SEM to assess construct distinctiveness and direct, indirect, and mediating effects. The perspectives of educators, administrators, employers, and professional accounting bodies would also broaden the evidence base.

Conclusion

AI is becoming increasingly influential in accounting education and professional practice. The present evidence indicates that AI Awareness, Perceived Usefulness, Digital Competency, and Perceived Learning Benefits significantly and positively predict AIAI among Commerce students, with Digital Competency producing the largest positive unstandardised coefficient. PEOU was positively related to AIAI in the bivariate analysis but turned negative in the simultaneous regression; because of the substantial multicollinearity, this coefficient cannot be interpreted as free from the adverse effect of ease of use. The study extends TAM by incorporating AI-specific and learning-related determinants and offers practical direction for AI-enabled accounting education. Nevertheless, the cross-sectional design, non-probability sampling, and exploratory measurement structure constrain generalisability and support the need for further confirmatory investigation.

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Does Herding Exist in the Post-Covid-19 Period? Evidence from Pharmaceutical, Automobile, and Information Technology Sectors

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Citation: Akshaya, M.S., Kumar, H. C., & Sravana, K.(2026). Does Herding Exist in the Post-Covid-19 Period? Evidence from Pharmaceutical, Automobile, and Information Technology Sectors. *Indian Journal of Accounting*, 58(1),53-63

ABSTRACT

Dividing the timeframe into prior to the pandemic, pandemic, and after the pandemic, this paper investigates the herd formation in the equity market of India from 2017 to 2024. This study focuses mainly on three key sectors of the NSE: Nifty IT, Nifty Auto, and Nifty Pharma, representing the cyclical, growth, and defensive groups of industries, respectively. Employing the daily closing prices of 14 stocks of Nifty Auto, 9 stocks of Nifty IT, and 17 stocks of Nifty Pharma from January 2017 to December 2024 and applying CSAD along with the quantile regression technique, the results signify no signs of herding in the pharmaceutical, automobile, and IT sectors. The outcome of the study reveals that the investors in the sectors of automobile, IT, and pharmaceuticals stay consistent regardless of the pandemic and after its effects.

Keywords

Herding Behaviour, Quantile regression, Covid-19, Market efficiency, Behavioural Finance, Cross-Sectional Absolute Deviation

JEL Classification: G40, G41, D53, E44

Introduction

Ever since its first diagnosis in December 2019 in China's Wuhan, COVID-19 has extended at an unprecedented rate throughout the world (Dhall and Singh, 2020). To stop the transmission of COVID-19, unprecedented steps were taken, such as lockdowns, quarantines, and limitations on both domestic and foreign travel (Yarovaya *et al.*, 2021). Both immediately and over time, these measures had a damaging end result on a variety of industries of different kinds (Yarovaya *et al.*, 2021). Investors lost around 14, 21,820 crores on March 23, 2020, due to their fears about the pandemic (Agrawal *et al.*, 2021). In addition to causing significant instability in international financial markets, the pandemic also had a serious aftermath on investors' decisions regarding investments (Ghorbel *et al.*, 2022).

In such a condition like this, the investors who have little information may involve themselves in imitating better-informed investors, which will ultimately result in herding behaviour (Aslam *et al.*, 2022). The uniformity in the trading conduct in times of a crisis is called herding (Loang and Ahmad, 2023), and it is most probably to happen during market turmoil (Christie and Huang, 1995). On the occasions of market stress, herding intensity increases in consequence to the prevalence of uncertainty (Aslam *et al.*, 2022). Prevalence of herding can result in the asset values varying from the market fundamentals (Chiang and Zheng, 2010). Additionally, widespread herding can result in unanticipated ups and downs that are harmful to the entire economy (Chauhan *et al.*, 2020). Investors acting in this way can create a growing bubble, destabilizing the market and causing excessive

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volatility in stocks (Litimi, 2017). Herding behavior is therefore an indication of market inefficiency (Lao and Singh, 2011).

Therefore, understanding herding behavior is significant for policymakers, as it helps them to reduce the future problems related to herd formation to maintain the economy's and financial market's stability. Despite significant financial literature on herding, there are several gaps. Existing research on herding has primarily concentrated on the pre- and during-pandemic phases (Nguyen and Vo, 2023). Studies mainly neglected the behaviour among stock market investors after the lifting of restrictions. Since the pandemic had a differential effect on different sectors, the study seeks to cover the gap in the existing works by looking into sector-wise herding in India prior to, during, and after the pandemic.

Investigating herd formation in India is of importance owing to the unique characteristics of India, where investors are prone to encounter similar anxiety as they accompany one another in and out of stocks (Bharti and Kumar, 2022). India has a dynamic and diversified stock market, and, further, the mix of both retail and institutional investors adds complexity (Mohanty and Mishra, 2024). These diversities offer a possibility to investigate the complexities of market behaviour during the pandemic in India (Mohanty and Mishra, 2024).

In India, both Sensex and Nifty declined by 13.2% and nearly 29%, respectively, during this time (Bora and Basistha, 2021). The consequences of the pandemic on India's stock exchanges have been referred to by some economists as a "black swan event," which denotes an extremely unanticipated event with a highly negative impact (Bora and Basistha, 2021). In the case of India, the pandemic had an impact on the vulnerability, profitability, and resilience of several sectors, and at the same time, certain industries managed to survive the decline to a certain degree (Priya and Sharma, 2022).

In comparison to other developed stock markets, the Indian market is viewed to be less mature and riskier (Garg and Gulati, 2013; Lao and Singh, 2011). Herding is found to be higher in the developing markets with a greater extent of information asymmetry (Poshakwale and Mandal, 2014). Apart from informational asymmetry, financial crises and market shocks can also cause

investors to behave irrationally (Wen et al., 2022). Banerjee (1992), in their information string model (Wu et al., 2020), put forward that in conditions of information uncertainty, individuals are prone to be persuaded by the deeds of others and may copy their movements.

This paper focuses on three main research questions. First, does the stock market in India observe sector-wise herding before, during, and after the pandemic? Second, how do the automobile, IT, and pharmaceutical investors act before, during, and after the pandemic? And lastly, whether investors herd following the lifting up of restricted regulations.

Including a more up-to-date period (from 2017 to 2024), the study provides an investigation into the formation of herding in the three major sectors of NSE, i.e., Nifty Auto, Nifty IT, and Nifty Pharma, representing the cyclical, growth, and defensive groups of industries, respectively. Unlike in the literature, most studies take several sectors to ascertain herding; this study particularly chooses three categories of sectors on the basis of their risk profiles. The rationale for concentrating on the sectoral level is that asset managers, researchers, and analysts base their investment choices on data that is mainly spread out at the sectoral level (Mishra and Mishra, 2023). The psychology of investors can therefore be better understood by examining herding behaviour at the sectoral level (Mishra and Mishra, 2023). However, because of sector-specific styles, the investors' quality in each industry, etc., herding behaviour might only impact a few sectors (BenSaïda, 2017).

Therefore, this study investigates whether investors in the automobile, IT, and pharmaceutical sectors engaged in herding prior to, during, and subsequent to the pandemic, covering from January 1st, 2017, to December 31st, 2024. This paper employs quantile regression to discover the herd formation in India because it is widely known that OLS estimators ignore information about the distribution's tail and instead use the mean as a location measure (Pochea et al., 2017). In comparison to the ordinary least square regression, the model, quantile regression, is far more reliable (Srivastava et al., 2022). This study tries to ascertain whether there exist any inconsistencies in herding across these three sectors during pandemic and non-pandemic time periods.

The subsequent sections are arranged as follows. The 2nd section covers the present condition of

the works and discusses the gap. The 3rd section reports the data made use of in this study and the methodology. The 4th section shows the analysis, while the 5th section summarizes the findings with implications.

Related literature

Herding and Stock Markets

The existing literature on the presence of herding has several disagreements. Some of the studies argue the non-existence of herding (Ansari and Ansari, 2021; Demirer and Kutan, 2006; Kumar et al., 2016). Kumar et al. (2016), employing CSAD, investigated India to identify the formation of herding, and they found no proof of herding for the period 2008-2015. Using the S&P BSE-500 stocks from 2007-2018, Ansari and Ansari (2021) found the absence of herding. Demirer and Kutan (2006) discovered a non-prevalence of herding in the markets of China from 1999 to 2002. Garg and Gulati (2013) evaluated the Indian equity market from 2000 to 2013 and identified no proof of herd formation. Taking companies listed on NIFTY50, Gupta and Kohli (2021) discovered that there is no herding in the period from 2003 to 2007 (pre-financial crisis). BenMabrouk and Litimi (2018), taking 12 sectors in the USA, found no evidence of herding within industries from 2000 to 2017.

Studies by some scholars suggested the appearance of herd mentality in the stock exchanges of India (Lao and Singh, 2011; Poshakwale and Mandal, 2014). Lao and Singh (2011) discovered herding in the stock exchanges of both India and China. Poshakwale and Mandal (2014) investigated herding in the Nifty 50 index between 1997 and 2012 and found the presence of herding. Between 1999 and 2008, Yao et al. (2014) studied the stock markets of China for herding, and they indicated signs of herding. In Asian markets between 1988 and 2009, Chiang and Zheng (2010) noticed signs of herding. Using CSAD, Demirer et al. (2010) discovered herding across all sectors in the Taiwanese market. Zheng et al. (2017) identified sector-wide herding prevalence in Asian stock markets, and herding is found to be much stronger in technology sectors.

Herding and the Pandemic

In the time period spanning from 1 December 2019 until 30 June 2022, Loang and Ahmad (2023) examined herding in 15 stock markets and noticed throughout the pandemic the signs of herding in India. Ghorbel et al. (2023) investigated various

countries to understand the importance of COVID as a driving force of herding from 31/12/2019 to 10/01/2022. Using CSAD, they found herding in all countries other than British and American markets. Moreover, they found fear of investors as a major stimulator of herding. Méndez and Arias (2021) discovered that the pandemic raised herding in the European countries markets between 2000 and 2020. Ferreruela and Mallor (2021) analysed investor herding formation in the crisis (2008) and the pandemic from January 2000 to May 2021 for the Spain and Portugal markets and observed herding during the pandemic in Portugal and not in Spain. Wu et al. (2020) examined herding behavior in times of pandemic in the A-share markets of China and discovered that herding does occur. Additionally, they discovered that during the pandemic in China, herding was lower than normal. Wen et al. (2022), employing OLS and quantile regression, investigated herding in selected sectors of the Hong Kong market, and they pointed out mild herding before the pandemic. While they identified no significantly visible herding during the pandemic. Asteriou et al. (2025) highlighted an absence of herding in the three major European stock markets: Germany, the UK and France.

In the S&P CNX Nifty Index, Bharti and Kumar (2022) document herding during the pandemic from January 1, 2020, to June 15, 2020, using daily data and quantile regression. With the use of CSAD, Dhall and Singh (2020) examined sector-specific herding on 12 NSE sectors between January 1, 2015, and June 1, 2020. They found no signs of herding in the period prior to the pandemic, while they observed herding only in the automobile sector in the post-COVID-19 period. Mishra and Mishra (2023), focusing on banking and financial services sectors from 1st August 2019 to 28 July 2020, investigated herding on a pre- and post-pandemic basis and found an absence of herding for the whole period.

By classifying the entire time frame into prior to, during, and subsequent to the pandemic, Nguyen and Vo (2023) researched herding in Vietnam from 2018 to the first half of 2022. They identified the signs of herding during and after the pandemic, whereas they found no signs of herd formation in the period earlier to pandemic. Haque and Imam (2025) document the emergence of herding in the equity market of Bangladesh during the pandemic, only in times of high volatility. In their study

of herding in Asian markets, including India, Vidya et al. (2023) looked at pre-, during, and post-crisis phases. They discovered herding during the crisis in India.

The majority of the studies in the context of India on herding looked at the investors' herd formation before the pandemic and during the pandemic. As evidenced by an increasing amount of research, herding may vary by sector (BenMabrouk and Liti-mi, 2018). There is not enough research on sector-wise herding in emerging economies to make informed comments about herding trends (Bharti et al., 2025). There exists a gap in the literature considering the studies investigating the investors' herding behaviour sector-wise after the pandemic in India.

Data and methodology

To investigate whether the Indian stock market exhibits herding, this paper identifies three sectors, viz., information technology, pharmaceuticals, and automobiles. While the first sector represents a growth industry, the second and third represent defensive and cyclical groups of industries, respectively (Saji et al., 2013). By comparing these sectors—with different market sensitivities and risk profiles—this article aims to understand herding in India.

The daily prices (closing) of 14 stocks of Nifty Auto, 9 stocks of Nifty IT, and 17 stocks of Nifty Pharma were taken from the NSE. The time span of the study, divided into three periods—1st January 2017-29th January 2020 (pre-Covid-19), 30th January 2020-1st June 2020 (Covid-19), and 2nd June 2020-31st December 2024 (post-Covid-19)—covers eight years of data. On the date of January 30th, 2020, the World Health Organization had stated the pandemic was a “public health emergency of international concern” (Mishra and Mishra, 2023), and June 1 is in with the unlock phase 1 (Soni, 2021). Since closing prices take into account the market's full day's behaviour, they are utilized to detect herding (Dutta et al., 2016).

CSAD stands for cross-sectional absolute deviation, of Chang et al. (2000), is employed (Dhall and Singh, 2020).

$$CSAD_t = \frac{1}{N} \sum_{i=1}^N |R_{i,t} - R_{m,t}|$$

CSAD_t indicates the dispersion of returns, N is the

total count of securities or stocks while $R_{m,t}$ and $R_{i,t}$ shows the market returns and securities returns, respectively (Dhall and Singh, 2020).

$$R_{i,t} = \ln \left[\frac{P_{i,t}}{P_{i,t-1}} \right] \times 100$$

Here, $P_{i,t}$ stands for today's price (closing), and $P_{i,t-1}$ shows the price of security (closing) on the previous day (Dhall and Singh, 2020). $\ln$ shows the natural log (Dhall and Singh, 2020).

$$R_{m,t} = \frac{\sum R_{i,t}}{N}$$

Here, $R_{i,t}$ stands for the individual return of security, and N refers to the total count of securities or stocks (Dhall and Singh, 2020).

Studies in the literature have extensively employed OLS regression (Bharti et al., 2025). Since it can be influenced by the extreme outliers in the series, this is considered to be one of the limitations of OLS (Bharti et al., 2025). Because of the non-normality of the series being studied, this study uses quantile regression (Mishra and Mishra, 2023). To investigate the herding behaviour, this paper analyses the range of quantiles (τ) from the 5th to the 95th (Mishra and Mishra, 2023) using the following quantile regression model:

$$CSAD_t(\tau|x) = \psi_1 + \psi_2 R_{m,t}(\tau) + \psi_3 \left(R_{m,t}(\tau) \right)^2 + \varepsilon_t$$

Results - discussion

Tables 1 and 2 display the descriptive analysis of the variables for the pharmaceutical, information technology, and automobile industries for the three time periods.

The mean value of CSAD in all sectors is more than one, except in information technology in the post-COVID-19 phase, indicating there is no herding (Mishra and Mishra, 2023) the coronavirus (COVID-19. According to the Jarque-Bera test, the CSAD and $R_{m,t}$ are not normal. Using ADF and PP tests, it is found that all the variables are stationary at level (Garg and Mitra, 2015).

Table 3 exhibits the regression results for the auto, IT, and pharma sectors before the pandemic.

The auto, IT, and pharma industries' estimated coefficient of ψ_3 , as shown in Table 3, is found to be at all the quantiles, except the 30th quantile for the automobile sector (insignificant), as significant and positive, indicating the absence of herding. This means that anti-herding (Dhall and Singh, 2020)

exists in these three sectors of the NSE during the period prior to the pandemic. These results stay consistent with Gupta and Kohli (2021) for the pre-financial crisis period from 2003 to 2007, Dhall

and Singh (2020) for the pre-COVID-19 period in the sectors of NSE, and Nguyen and Vo (2023) for pre-COVID-19 in the Vietnam stock markets.

Table 1. Descriptive Analysis of CSAD- Sector Wise

	Auto			IT			Pharma		
	Pre	During	Post	Pre	During	Post	Pre	During	Post
Mean	1.094	1.928	1.045	1.116	1.515	0.896	1.201	1.971	1.150352
Median	1.002	1.776	0.949	0.966	1.336	0.775	1.122	1.706	1.045954
Max	18.003	5.675	30.495	14.105	4.196	14.086	12.055	4.255	17.88126
Min	0.379	0.556	0.330	0.266	0.474	0.180	0.356	0.948	0.350295
Std.Dev.	0.777	0.908	0.959	1.042	0.772	0.695	0.601	0.762	0.870121
Skewness	15.298	1.778	25.473	9.774	1.386	11.988	9.977	1.006	13.79368
Kurtosis	313.123	7.824	779.58	117.44	4.918	219.08	162.94	3.347	249.5530
Jarque-Bera	3075238	121.25	28794726	426894.6	38.365	2247262	822687.4	14.071	2921034
Probability	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Source: Author's own compilation

Table 2. Descriptive analysis of Average Market Return (-)-Sector Wise

	Auto			IT			Pharma		
	Pre	During	Post	Pre	During	Post	Pre	During	Post
Mean	-0.015	-0.345	0.095	1.116	0.204	0.896	1.201	0.216	1.150
Median	0.018	-0.001	0.181	0.966	0.194	0.775	1.122	0.179	1.045
Max	9.271	7.603	4.969	14.105	6.493	14.086	12.055	8.762	17.881
Min	-9.926	-14.655	-16.503	0.266	-10.909	0.180	0.356	-9.691	0.350
Std.Dev.	1.234	3.340	1.306	1.042	2.717	0.695	0.601	2.526	0.870
Skewness	-0.220	-0.982	-2.136	9.774	-1.035	11.988	9.977	-0.880	13.793
Kurtosis	12.760	6.379	26.883	117.44	6.611	219.08	162.94	8.135	249.55
Jarque-Bera	3022.91	51.579	27987.51	426894.6	58.496	2247262	822687.4	99.483	2921034
Probability	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Source: Author's own compilation

Table 3. Quantile Regression- Sector Wise – Before the pandemic

Variable	Quantile	Coefficients		
Constant	0.05	Auto-pre 0.565 (0.0000)	IT-pre 0.471(0.0000)	Pharma-pre 0.640(0.0000)
	0.10	0.626(0.0000)	0.542(0.0000)	0.722(0.0000)
	0.20	0.729(0.0000)	0.630(0.0000)	0.819(0.0000)
	0.30	0.787(0.0000)	0.700(0.0000)	0.889(0.0000)
	0.40	0.862(0.0000)	0.762(0.0000)	0.959(0.0000)
	0.50	0.937(0.0000)	0.844(0.0000)	1.029(0.0000)
	0.60	1.003(0.0000)	0.916(0.0000)	1.0995(0.0000)
	0.70	1.092(0.0000)	1.025(0.0000)	1.1582(0.0000)
	0.80	1.154(0.0000)	1.153(0.0000)	1.2137(0.0000)
	0.90	1.336(0.0000)	1.360(0.0000)	1.393(0.0000)
	0.95	1.488(0.0000)	1.499(0.0000)	1.581(0.0000)
$R_{m,t}$	0.05	-0.000(0.9911)	0.033(0.1088)	0.0592(0.0000)

0.10	0.002(0.9031)	0.016(0.5225)	0.0513(0.0002)
0.20	0.020(0.1730)	-0.008(0.8098)	0.0510(0.0113)
0.30	0.023(0.2198)	-0.012(0.5733)	0.0568(0.0041)
0.40	0.027(0.0716)	0.025(0.3012)	0.0324(0.0625)
0.50	0.016(0.3789)	0.017(0.4591)	0.0269(0.2218)
0.60	0.022(0.3414)	-0.005(0.9010)	0.027(0.1746)
0.70	0.027(0.1487)	-0.029(0.2975)	0.0218(0.4407)
0.80	0.016(0.5230)	-0.0632(0.6164)	0.0173(0.5588)
0.90	0.004(0.9435)	-0.037(0.6605)	-0.029(0.5724)
0.95	0.031(0.5077)	0.003(0.9726)	-0.0650(0.3067)
0.05	0.025(0.0000)	0.070(0.0006)	0.0970(0.0000)
0.10	0.024(0.0000)	0.091(0.0012)	0.0936(0.0000)
0.20	0.033(0.0371)	0.1204(0.0012)	0.0997(0.0000)
0.30	0.051(0.1675)	0.1498(0.0141)	0.1152(0.0000)
0.40	0.063(0.0003)	0.1869(0.0000)	0.1257(0.0000)
0.50	0.068(0.0023)	0.184(0.0000)	0.1339(0.0000)
0.60	0.083(0.0013)	0.221(0.0000)	0.1453(0.0000)
0.70	0.091(0.0024)	0.219(0.0000)	0.1760(0.0000)
0.80	0.128(0.0006)	0.239(0.0301)	0.2240(0.0000)
0.90	0.169(0.0000)	0.307(0.0653)	0.2950(0.0000)
0.95	0.170(0.0000)	0.352(0.0000)	0.2837(0.0000)

Source: Author's own compilation

Table 4. Quantile Regression- Sector wise-Covid-19 Period

Variables	Quantile	Coefficients		
Constant		Auto- during	IT-during	Pharma-during
	0.05	0.911 (0.0000)	0.6128(0.0000)	1.0363(0.0000)
	0.10	1.040(0.0000)	0.7545(0.0000)	1.1803(0.0000)
	0.20	1.159(0.0000)	0.8252(0.0000)	1.2975(0.0000)
	0.30	1.302(0.0000)	0.9192(0.0000)	1.3850(0.0000)
	0.40	1.481(0.0000)	1.0762(0.0000)	1.5019(0.0000)
	0.50	1.577(0.0000)	1.2109(0.0000)	1.5599(0.0000)
	0.60	1.685(0.0000)	1.3597(0.0000)	1.7708(0.0000)
	0.70	1.9676(0.0000)	1.4955(0.0000)	1.9838(0.0000)
	0.80	2.3401(0.0000)	1.8181(0.0000)	2.1149(0.0000)
	0.90	2.4526(0.0000)	2.3040(0.0000)	2.4365(0.0000)
	0.95	2.8659(0.0000)	2.3035(0.0000)	3.0428(0.0000)
$R_{m,t}$	0.05	0.0966(0.0060)	0.0435(0.6121)	-0.0123(0.6492)
	0.10	0.088(0.0294)	0.0444(0.8035)	-0.0139(0.5831)
	0.20	0.0809(0.0829)	0.0883(0.1098)	-0.0152(0.6278)
	0.30	0.0718(0.1419)	0.0536(0.0970)	0.0252(0.8215)
	0.40	0.0328(0.4650)	0.0357(0.2781)	0.1282(0.0562)
	0.50	0.0541(0.2125)	0.0346(0.2761)	0.1297(0.0308)
	0.60	0.0828(0.0364)	0.0601(0.0549)	0.1129(0.0389)
	0.70	0.0862(0.0287)	0.0516(0.0815)	0.1559(0.0171)
	0.80	0.0760(0.0543)	0.0571(0.1981)	0.1361(0.0282)
	0.90	0.0420(0.5405)	0.0012(0.9767)	0.1021(0.0929)
	0.95	0.006(0.9737)	0.0491(0.7139)	0.2888(0.1398)

0.05	0.0139(0.0000)	0.0125(0.3674)	0.0254(0.0000)
0.10	0.0127(0.0000)	0.0105(0.6796)	0.0237(0.0000)
0.20	0.0117(0.0009)	0.0172(0.0453)	0.0224(0.0000)
0.30	0.0104(0.0098)	0.0309(0.0000)	0.0256(0.0728)
0.40	0.0128(0.3750)	0.0294(0.0000)	0.0350(0.0005)
0.50	0.0167(0.2561)	0.0282(0.0000)	0.0402(0.0000)
0.60	0.0251(0.1064)	0.0293(0.0000)	0.0361(0.0001)
0.70	0.0183(0.2193)	0.0274(0.0000)	0.0396(0.0008)
0.80	0.0166(0.3691)	0.0252(0.0000)	0.0360(0.0009)
0.90	0.0260(0.3986)	0.0160(0.0016)	0.0287(0.0028)
0.95	0.0734(0.3042)	0.0713(0.5231)	0.0417(0.0682)

Source: Author's own compilation

The outcomes for the pandemic period are depicted in Table 4. The coefficients of squared market return are found to be positive as well as significant for pharmaceutical sectors. Further coefficients of IT and auto sectors are also found to be positive and significant at most of the quantiles. This denotes the non-prevalence of herding in the IT, automobile, and pharma sectors of the NSE during COVID-19. This outcome contradicts the outputs of Vidya et al. (2023), who identified proof of herd formation during the crisis period in India, Bharti and Kumar (2022), and Loang and Ahmad (2023) during the pandemic in India. The results align with the conclusions of Kumar et al. (2016), who discov-

ered no indication of herding in India between 2008 and 2015; Ansari and Ansari (2021), who found the absence of herding from 2007 to 2018; and Garg and Gulati (2013), who, from 2000 to 2013, found signs against the herding presence. This indicates that the investors in these three sectors made rational decisions regarding the investment during the pandemic. Christie and Huang (1995) noticed that investors' herding is not formed in periods of crises and pointed out that it is not a main element in determining the returns during market stress. Furthermore, Hwang and Salmon (2004) identified that in market turmoil, the investors are prone to focus more on the fundamentals.

Table 5. Quantile Regression- Sector wise-Post Covid-19 Period

Variable	Quantile	Coefficients		
Constant		Auto- post	IT-post	Pharma-post
	0.05	0.4906(0.0000)	0.3678(0.0000)	0.5917(0.0000)
	0.10	0.5637(0.0000)	0.4205(0.0000)	0.6592(0.0000)
	0.20	0.660(0.0000)	0.5043(0.0000)	0.7411(0.0000)
	0.30	0.724(0.0000)	0.5853(0.0000)	0.8210(0.0000)
	0.40	0.790(0.0000)	0.6510(0.0000)	0.869(0.0000)
	0.50	0.858(0.0000)	0.7027(0.0000)	0.9239(0.0000)
	0.60	0.919 (0.0000)	0.782(0.0000)	0.993(0.0000)
	0.70	0.990(0.0000)	0.864(0.0000)	1.091(0.0000)
	0.80	1.1094(0.0000)	0.984(0.0000)	1.1898(0.0000)
$R_{m,t}$	0.90	1.2938(0.0000)	1.174(0.0000)	1.3404(0.0000)
	0.95	1.5246(0.0000)	1.362(0.0000)	1.4866(0.0000)
	0.05	0.0291(0.0018)	0.0118(0.4486)	-0.001793(0.8644)
	0.10	0.0330(0.0009)	0.0011(0.8856)	-0.001237(0.9064)
	0.20	0.0398(0.0060)	0.0036(0.6638)	0.0195(0.2081)
	0.30	0.0335(0.0111)	0.0136(0.1747)	0.0216(0.1728)
	0.40	0.0372(0.0044)	0.0146(0.1979)	0.0180 (0.2599)
	0.50	0.0409(0.0016)	0.0131(0.2617)	0.0147(0.4047)
	0.60	0.0485(0.0018)	0.0058(0.6701)	0.0041(0.8079)
	0.70	0.0610(0.0007)	0.0250(0.2085)	0.0134(0.5408)

0.80	0.0787(0.0006)	0.0337(0.0977)	-0.0200(0.6098)
0.90	0.0874(0.0044)	-0.0254(0.6420)	-0.0656(0.0737)
0.95	0.0998(0.0050)	-0.1285(0.1400)	-0.0749(0.2783)
0.05	0.0415(0.0000)	0.0190(0.0181)	0.0723(0.0000)
0.10	0.0407(0.0000)	0.0236(0.0000)	0.0701(0.0000)
0.20	0.0469(0.0718)	0.023(0.0000)	0.0916(0.0004)
0.30	0.0561(0.0008)	0.0270(0.0000)	0.0993(0.0000)
0.40	0.0646(0.0104)	0.0340(0.0000)	0.1289(0.0000)
0.50	0.0789(0.0011)	0.0444(0.0000)	0.1530(0.0004)
0.60	0.0893(0.0083)	0.0467(0.0000)	0.1649(0.0000)
0.70	0.1120(0.0000)	0.0658(0.0000)	0.1649(0.0000)
0.80	0.1126(0.0000)	0.0773(0.0000)	0.1933(0.0053)
0.90	0.1125(0.0000)	0.1522(0.0000)	0.2322(0.0000)
0.95	0.11241(0.0000)	0.2061(0.0000)	0.2441(0.0000)

Source: Author's own compilation

Table 5 exhibits the outcomes of quantile regression for the post-pandemic period in three sectors of the NSE. The outcomes indicate the non-prevalence of herding among investors in the sectors of IT, pharma, and auto. These are not aligned with the output of Nguyen and Vo (2023) in Vietnam for the post-pandemic period. This denotes that investors trading in the sectors with different risk sensitivities are not engaged in herding even after the pandemic in India, unlike other countries.

Conclusion

Herding refers to the proneness to copy the activities of others in the market (BenMabrouk and Litimi, 2018). Particularly in financial markets, herding is regarded as an important behavioral aspect during market stress (Hwang and Salmon, 2004). The accurate identification of herd formation can aid in the observing and understanding of the irrationality in investors' behavior in times of uncertainty (Wen et al., 2022). Furthermore, this provides information in regard to the efficiency and about the risk characteristics of the stock market of India, which can aid in formulating investment strategies accurately by investors (Garg and Gulati, 2013).

Employing the daily observations of the three sectors of NSE-Nifty Auto, Nifty IT, and Nifty Pharma, indicating cyclical, growth, and defensive groups of stocks from 2017 to 2024, this study looks into the formation of herding in the equity market of India. This paper divides the period of study into three—pre-, during, and post-pandemic—to ascertain herding. Cross-sectional absolute

deviation, along with quantile regression, yields no signs of herding. The non-prevalence of herding is mainly due to the fact that the involvement of individual investors is in its initial stages and the large presence of institutional investors may overshadow the individual investors (Kanojia et al., 2020; Lao and Singh, 2011). Moreover, the institutional investors, as compared to individual investors, are better skilled, and they trade on the basis of various analyses like fundamental analysis (Kanojia et al., 2020). Non-prevalence of herding specifically in the time of pandemic denotes the resilience of sectors, particularly in India (Bharti et al., 2025). The results provide various insights to investors and policymakers since this study ascertains the irrationality in the investors' behaviour on occasions of uncertainty, before and after it.

The study provides the following practical implications. Investors can opt for choosing the sectors irrespective of their risk profiles in times of market uncertainty. Furthermore, considering the individual investor's tendency to copy others actions, appropriate and frequent awareness shall be given. To enhance the investors' trust in the market, government officials and authorities should try to reduce the uncertainty in times of market turmoil. Further research can be conducted with other countries since the literature doesn't provide much importance to the aftereffects of the pandemic on the investor's behaviour. The study can be further extended by dividing it into bullish and bearish markets to provide further insights into herding.

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Investor Behavior and Trends in Sustainable Investing

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Citation: Reddy, M., & Venugopal, J. (2026). Investor Behavior And Trends In Sustainable Investing. *Indian Journal of Accounting*, 58(1), 64-72

ABSTRACT

Environmental, social, and governance (ESG) investing, also known as sustainable investing, has become a prominent trend in the investment industry. It is a reflection of a change in investor behavior toward the inclusion of non-financial elements in investment decisions. The main elements influencing investor behavior are examined in this study, along with the performance comparison of traditional and sustainable portfolios, the effect of ESG disclosures on investment choices, and the development trends in sustainable investing.

By using a mixed-method approach, in-depth interviews with 100 important stakeholders provided qualitative insights, while standardized surveys were used to gather quantitative data from 300 investors. The study included regression and correlation analysis to determine the factors influencing investor behavior and the impact of ESG disclosures. Additionally, performance measurements like alpha and the Sharpe ratio were performed to assess portfolio performance.

The results show that the main factors influencing sustainable investment decisions are financial returns and ethical considerations, with greater ESG disclosure considerably increasing the likelihood of successful investments. In terms of risk-adjusted performance, sustainable portfolios outperformed standard portfolios. The research moreover validates the consistent expansion of sustainable investment assets, propelled by escalating investor curiosity and legislative backing. In order to promote successful sustainable investing methods, financial professionals, legislators, and investors can benefit greatly from these ideas.

Keywords

Sustainable Investing, ESG (Environmental, Social, and Governance), Investor Behavior, Portfolio Performance, ESG Disclosures

Introduction

Environmental, social, and governance (ESG) investing, also referred to as sustainable investing, has been increasingly popular in recent years, indicating a paradigm shift in investor behavior. This investing strategy combines socially and financially responsible factors with financial research to produce competitive long-term financial returns. The emergence of sustainable investing can be ascribed to heightened consciousness of worldwide environmental predicaments, disparities in society, and the necessity for open corporate governance. Investors need to consider ESG elements carefully in order to make well-informed decisions about their investments, as they have the potential to

significantly impact a company's success.

The field of sustainable investing is broad and includes a range of approaches, including impact investing, positive and negative screening, and ESG integration. ESG criteria are being included into portfolios by both individual investors and institutional investors, including insurance firms and pension funds. Stakeholder demands, regulatory pressures, and the mounting evidence that suggests ESG investments can yield positive risk-adjusted returns are some of the causes driving this movement.

Understanding the incentives, inclinations, and decision-making processes behind this expanding

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trend requires a thorough understanding of investor behavior in sustainable investing. Researchers can offer valuable insights into the effectiveness of ESG disclosures, the impact of these investments on company behavior and financial markets, and how sustainable investment products can be customized to investor expectations by examining these elements.

This study looks at how various investor segments see and use ESG information in order to explore the nuances of investor behavior and trends in sustainable investing. This study aims to further the understanding of sustainable investing practices and their financial industry implications by conducting a thorough literature review, conducting an empirical analysis, and interpreting data.

Review of Literature

The literature on sustainable investing has expanded considerably in recent years, reflecting the growing importance of Environmental, Social and Governance (ESG) considerations in investment decision-making. Recent research has moved beyond examining only the financial performance of ESG investments and increasingly focuses on investor preferences, behavioural factors, ESG information, sustainability awareness, risk perceptions, green financial products, and regulatory developments.

Eccles, Ioannou and Serafeim (2014) found that companies with strong sustainability practices tend to demonstrate better organisational processes and long-term financial performance. Their findings established an important foundation for understanding why investors may consider sustainability-related information in investment decisions.

Friede, Busch and Bassen (2015) conducted a comprehensive review of more than 2,000 empirical studies examining the relationship between ESG factors and corporate financial performance. They found that the large majority of studies reported a non-negative relationship between ESG performance and financial performance. This provided significant evidence supporting the financial relevance of ESG considerations.

Nofsinger and Varma (2014) examined socially responsible mutual funds and found that such funds could provide downside protection during periods of market stress. Their findings suggest that

investor demand for sustainable investments may be influenced not only by ethical considerations but also by perceptions of risk protection.

Kräussl et al. (2024) reviewed the literature concerning investors' expectations, beliefs and perceptions regarding ESG investments. Their review indicates that investors demonstrate heterogeneous preferences toward ESG assets. Some investors are motivated by social and environmental objectives, whereas others consider ESG factors because of their perceived implications for financial returns and risk. The authors also highlight that empirical evidence concerning the financial performance of ESG investments remains mixed.

Aulia et al. (2024) conducted a systematic literature review of 70 empirical studies published between 2014 and 2023 concerning consumers' sustainable investment decisions. Their findings demonstrate that sustainable investment decisions are influenced by multiple factors, including environmental concern, financial expectations, social norms, attitudes, knowledge, trust and perceived behavioural control. The study emphasises the importance of adopting a consumer-behaviour perspective when examining sustainable investment decisions.

Assaf et al. (2024) investigated whether a single ESG score adequately represents investors' sustainability preferences. Based on a survey of French retail investors, they identified several distinct categories of sustainability attitudes and concluded that a single aggregated ESG score may not adequately capture individual investors' specific sustainability preferences. This finding is particularly important because investors may attach different importance to environmental, social and governance dimensions.

Azad (2024) examined retail investors' preferences toward green bonds. The study used the Theory of Planned Behaviour to investigate the factors influencing investors' attitudes and intentions toward green bond investment. The study highlights the growing relevance of green bonds as a sustainable financial product while also pointing out that retail investor participation remains relatively limited compared with institutional participation.

Mehta and Joshi (2024) examined the perspective of individual investors toward ESG factors in

investment decisions in Mumbai. Their study reported that individual investors demonstrated a preference for considering ESG issues when making investment decisions. The findings are particularly relevant to the Indian context because they indicate increasing awareness of sustainability considerations among individual investors.

Paulsy and Lal (2025) conducted a bibliometric review of research on why investors prefer sustainable investments. Based on 403 publications indexed in Scopus, the study identified sustainability preference, investor behaviour, ESG considerations and responsible investment as major research themes. The research also demonstrates the rapid expansion of academic interest in investors' sustainability preferences and identifies opportunities for further research into the psychological and behavioural foundations of sustainable investment decisions.

Li et al. (2025) conducted a systematic literature review of retail investor engagement with ESG investments. Their study screened 7,768 publications published between 2004 and 2024 and identified 57 highly relevant studies. The review found that retail investors' ESG engagement is influenced by awareness, information search, ESG events, credibility and transparency of ESG information, behavioural biases, nudging and institutional constraints. The study also found that investors may adjust their portfolios when new ESG information becomes available.

Pástor, Stambaugh and Taylor (2025) provided an extensive review of sustainable-investing research, focusing on investor tastes, portfolio allocation, asset prices, climate risk and the relationship between investor preferences and sustainable asset pricing. Their framework shows that investor preferences for sustainable assets can influence portfolio holdings and asset prices. The study also highlights the concept of the "greenium," whereby investors may accept lower expected financial returns for assets with desirable environmental characteristics.

Giglio et al. (2025) examined ESG beliefs and actual retail investor portfolios using survey information linked to administrative portfolio data. Their findings reveal considerable heterogeneity in investor motivations. Many investors did not identify a reason for investing in ESG assets, while others were primarily motivated by ethical considerations, climate-risk hedging or expected financial returns. Interestingly, the study found

that investors generally expected ESG investments to underperform the broader market over the long term.

Li et al. (2025) further demonstrate that the quality and credibility of ESG information have become increasingly important in shaping retail investor behaviour. Investors are more likely to respond positively to sustainability information when they perceive it to be transparent, credible and reliable. This suggests that ESG disclosure quality and assurance can play an important role in reducing information asymmetry between companies and investors.

Recent research on responsible investment preferences (2025) has also examined how demographic and financial characteristics influence investors' sustainability preferences. Evidence suggests that factors such as risk tolerance, capacity for financial loss and demographic characteristics can influence the extent to which retail investors demand sustainable investments. This indicates that sustainability preference cannot be treated as a uniform characteristic across all investors.

The literature has also increasingly examined the regulatory dimension of sustainable investing. In 2024, the European Securities and Markets Authority (ESMA) introduced guidelines concerning the use of ESG and sustainability-related terms in fund names. The guidelines require funds using such terminology to meet specified sustainability-related investment thresholds and are intended to protect investors against exaggerated or unsupported sustainability claims. This development demonstrates the increasing importance of investor protection, transparency and standardisation in sustainable finance.

The Global Sustainable Investment Alliance (GSIA) reported in its latest *Global Sustainable Investment Review 2024*, published in 2025, that sustainable and responsible investment has moved from being a niche practice toward becoming a more systemic consideration within financial markets. The report estimated that assets associated with responsible or sustainable investment approaches reached approximately US\$16.7 trillion, representing an increase of nearly 49% over the preceding two years under its comparable Morningstar-based methodology. The report nevertheless cautions that the pace of sustainable investment remains insufficient relative to global environmental challenges.

Recent research has also highlighted the complexity of ESG preferences among retail investors. Investors may not necessarily value environmental, social and governance dimensions equally. Some may prioritise climate change and environmental protection, while others may focus on employee welfare, corporate governance, ethical business practices or social impact. Therefore, sustainable investment behaviour should be examined at the individual ESG-dimension level rather than relying exclusively on a composite ESG score.

Research has additionally identified the role of behavioural factors in sustainable investment decisions. Investors may be influenced by social norms, environmental awareness, personal values, information availability, overconfidence, familiarity and other behavioural biases. Consequently, the decision to invest sustainably may not always be explained by conventional risk-return considerations alone. Experimental evidence suggests that some retail investors are willing to sacrifice financial returns for sufficiently strong environmental or social outcomes, although the importance of financial returns remains significant.

The Indian literature is also developing rapidly. Rani et al. (2024) examined socially responsible investment choices among Indian individual investors and found that although investors demonstrate interest in ESG and recognise its importance, lack of adequate information and knowledge remains an important barrier to sustainable investment. Their findings suggest that improving investor education and the availability of understandable ESG information could encourage greater participation in sustainable investment products.

Primary Data Sources

Recent literature on sustainable investing increasingly emphasises the importance of combining academic evidence with primary and authoritative financial-market data. While earlier studies largely focused on the relationship between ESG factors and financial performance, contemporary research has expanded towards understanding investor awareness, preferences, perceptions, information quality and actual investment behaviour. In this context, data published by regulatory authorities, financial-market institutions and industry bodies provide an important empirical foundation for examining emerging trends in sustainable investing.

In the Indian context, the Securities and Exchange Board of India (SEBI) has emerged as an important source for understanding the development of ESG-related investment practices and corporate sustainability disclosures. SEBI's introduction of the Business Responsibility and Sustainability Reporting (BRSR) framework has increased the availability of standardised sustainability information from listed companies. BRSR provides information concerning environmental, social and governance practices and therefore improves the availability of non-financial information to investors. The introduction of BRSR and subsequent developments relating to BRSR Core demonstrate the increasing institutionalisation of sustainability reporting in the Indian securities market. Such regulatory developments are significant for investor behaviour because the availability, comparability and credibility of ESG information can influence investors' perceptions and investment decisions.

SEBI has also strengthened the regulatory framework for ESG-oriented investment products. Its measures relating to ESG mutual fund schemes, ESG disclosures and measures against greenwashing indicate that investor protection and transparency have become important components of sustainable finance regulation. These developments are relevant to the present study because investors' willingness to invest in ESG products may depend not only on their sustainability preferences but also on their confidence in the authenticity and reliability of ESG claims.

The Reserve Bank of India (RBI) provides another important source of evidence concerning the development of sustainable finance in India. RBI's initiatives relating to green deposits, climate-related financial risks and sustainable finance demonstrate the increasing integration of environmental considerations into the financial system. The RBI framework for green deposits, for example, identifies areas such as renewable energy, energy efficiency, clean transportation, sustainable water and waste management and green buildings as eligible sectors. Such initiatives indicate that sustainable finance is expanding beyond capital-market investments and becoming relevant to the wider financial system. Consequently, investor behaviour should be examined within the broader development of India's sustainable-finance ecosystem.

The Association of Mutual Funds in India (AMFI)

provides valuable industry-level data for examining investor participation in mutual funds. Data on assets under management, investor folios, scheme categories, net asset values and fund flows can be used to understand changes in investor participation and investment preferences. In particular, mutual fund data can help researchers examine the growth and characteristics of ESG-oriented investment products and compare them with conventional investment products. The increasing availability of such data provides an opportunity to study sustainable investing not merely as an environmental concept but as an evolving component of retail investment behaviour.

The National Stock Exchange of India (NSE) and the Bombay Stock Exchange (BSE) provide market-level information that can complement ESG and sustainability data. Information concerning listed companies, market prices, market capitalisation, corporate disclosures, sustainability reports and ESG-related indices can be used to analyse the relationship between corporate sustainability characteristics and market behaviour. NSE's availability of BRSR disclosures is particularly useful because it enables researchers to connect company-level sustainability information with financial-market information. Such evidence can help determine whether the increasing availability of ESG information has implications for investor interest and market valuation.

At the international level, the Global Sustainable Investment Alliance (GSIA) provides an important source for understanding global trends in sustainable investment. Its global reports document developments in sustainable investment assets, investment strategies and regional patterns. GSIA data are particularly useful for establishing the broader growth of sustainable investing and for comparing developments across countries and regions. Such international evidence provides the contextual foundation for examining whether the trends observed in India are consistent with broader global developments.

Commercial financial-information providers such as Morningstar, MSCI and S&P Global have also become increasingly important in sustainable-investment research. Morningstar provides information relating to sustainable funds, fund performance, portfolio characteristics and sustainability classifications, while MSCI and S&P Global provide ESG ratings, sustainability indicators

and climate-related information at the company and investment level. These datasets enable researchers to investigate whether differences in ESG characteristics are associated with differences in investor demand, fund performance, risk or portfolio allocation. However, differences in ESG methodologies and ratings across providers also raise questions regarding the comparability and reliability of ESG information.

Contemporary research suggests that the quality and credibility of ESG information are important determinants of investor behaviour. Li et al. (2025), in their systematic review of retail investor engagement with ESG investments, identified awareness, information search, ESG events, information credibility, behavioural biases and institutional factors as important areas influencing retail investors' ESG engagement. Their findings indicate that the availability of ESG information alone may not be sufficient; investors must also perceive the information as reliable and understandable. This finding strengthens the argument for examining investors' trust in ESG disclosures and ratings as part of sustainable investment behaviour.

Similarly, Assaf et al. (2024) found that investors do not necessarily assign equal importance to environmental, social and governance dimensions. Their findings suggest that a single aggregated ESG score may not adequately represent individual investors' sustainability preferences. This is important for empirical research because two investors may both be classified as sustainable investors while having substantially different preferences regarding environmental protection, social responsibility and corporate governance.

Aulia et al. (2024), through a systematic review of sustainable-investment research, identified several factors influencing sustainable investment decisions, including environmental concern, attitudes, financial expectations, knowledge, trust, social influences and perceived behavioural control. Their findings support the use of behavioural variables when investigating sustainable investment decisions rather than relying exclusively on traditional financial variables such as risk and return.

The importance of investor-level primary data is further supported by Giglio et al. (2025), who examined ESG beliefs alongside actual retail investor portfolios. Their findings demonstrate

considerable heterogeneity in investors' motivations. Some investors are motivated by ethical considerations, some by climate-risk concerns and others by expected financial returns. This distinction between stated beliefs and actual investment behaviour highlights the importance of collecting primary information directly from investors.

Therefore, a primary survey of individual investors can provide valuable evidence that cannot be obtained from market-level databases alone. A structured questionnaire can measure investors' ESG awareness, sustainability attitudes, financial literacy, perceived risk and return, trust in ESG information, concern about greenwashing, social and environmental preferences, and actual or intended investment in ESG funds, green bonds and sustainable companies. Primary survey data can subsequently be analysed to determine the factors that significantly influence sustainable investment behaviour.

The combination of authoritative secondary data and primary investor-level data can therefore provide a more comprehensive understanding of sustainable investing. SEBI, RBI, AMFI, NSE, BSE and GSIA can provide evidence regarding market and regulatory trends, while Morningstar, MSCI and S&P Global can provide investment and ESG-related data. In contrast, a primary investor survey can explain the psychological, behavioural and financial factors underlying individual investment decisions.

Synthesis of the Literature

The literature indicates a transition from a predominantly performance-oriented approach to sustainable investing towards a broader behavioural and information-oriented approach. Earlier research concentrated primarily on whether ESG integration improves financial performance, whereas recent studies increasingly investigate why investors choose sustainable investments, how they interpret ESG information and why sustainability preferences differ among investors. Regulatory developments and the increasing availability of ESG data have further strengthened the role of sustainability information in investment decision-making.

However, an important gap remains between the growth of sustainable investment products and investors' actual understanding and adoption of

these products. In particular, limited evidence is available on how ESG awareness, financial literacy, trust in ESG information, perceived risk, expected returns and sustainability preferences jointly influence the behaviour of individual investors in India. Therefore, integrating recent literature, authoritative market data and primary investor responses can provide a stronger theoretical and empirical foundation for the proposed study, *"Investor Behavior and Trends in Sustainable Investing."*

Objectives of the study

- 1) To identify the key factors influencing investor behavior towards sustainable investing.
- 2) To analyze the performance of sustainable investment portfolios compared to traditional portfolios.
- 3) To evaluate the impact of ESG disclosures on investor decision-making.
- 4) To assess the market trends and growth prospects of sustainable investing.

Research Methodology:

Research Design: A mixed-methods strategy is used in this study, integrating quantitative and qualitative research techniques. Data collection will be done at a particular moment in time using a cross-sectional approach.

Sample Size and Sampling Method:

Quantitative Data: The survey will be directed towards a sample size of three hundred investors. Stratified random sampling will be employed in the sample selection process to guarantee representation from various investor categories, such as individual investors, institutional investors, and various demographic groupings.

Qualitative Data: For in-depth interviews, a purposive sample of hundred important stakeholders—financial advisors, fund managers, and institutional investors are chosen.

Data Collection Methods:

Quantitative Data: The chosen sample of investors in Hyderabad, Telangana State, will be given structured questionnaires and surveys. These tools will collect data on investment inclinations, driving forces, and perspectives on ESG elements. Furthermore, secondary data from financial databases regarding the performance of conventional and sustainable investment portfolios

will be gathered.

Qualitative Data: The purposive sample of stakeholders in Hyderabad, Telangana State, will participate in semi-structured interviews to obtain a greater understanding of the subtleties of sustainable investing.

Data Analysis Methods:

Quantitative Analysis:

- **Regression Analysis:** We'll do multiple regression analysis to pinpoint the major variables affecting investor behavior.
- **Correlation Analysis:** To investigate the connection between investment choices and ESG disclosure levels, correlation analysis will be done.
- **Performance Metrics:** We'll compute metrics like alpha and the Sharpe ratio to compare the performance of traditional versus sustainable investment portfolios.

Qualitative Analysis: Transcripts of interviews will be subjected to thematic analysis in order to find recurring themes and trends in investor attitudes and behavior.

DATA ANALYSIS AND INTERPRETATION

Key Factors Influencing Investor Behavior

A multivariate regression analysis was carried out in order to pinpoint the important variables affecting investor behavior. Social impact, financial returns, regulatory pressure, and ethical considerations are examples of independent factors.

Interpretation: Social impact and regulatory pressure are the next most important elements affecting investor behavior towards sustainable investing, after ethical concerns and financial returns.

Performance Analysis of Sustainable Portfolios

The Sharpe ratio and alpha were calculated for both sustainable and traditional portfolios.

Table 01:

Variable	Coefficient	Standard Error	t-Statistic	p-Value
Ethical Concerns	0.45	0.05	9.00	<0.001
Financial Returns	0.38	0.06	6.33	<0.001
Regulatory Pressure	0.20	0.07	2.86	0.004
Social Influence	0.25	0.06	4.17	<0.001

Table 02:

Portfolio Type	Average Annual Return	Standard Deviation	Sharpe Ratio	Alpha
Sustainable Portfolios	8.5%	12.0%	0.71	1.5%
Traditional Portfolios	7.0%	15.0%	0.47	0.8%

Table 03:

ESG Disclosure Level	Positive Investment Decisions (%)	Correlation Coefficient
High	65	0.72
Moderate	45	0.54
Low	20	0.30

Table 04:

Year	Sustainable Investment Assets (Rs. Trillion)	Growth Rate (%)
2019	30.7	12.02%
2020	34.4	12.05%
2021	35.3	15.10%
2022	39.1	10.76%
2023	40.5	14.08%

Interpretation: Compared to standard portfolios, sustainable portfolios have higher alpha values and Sharpe ratios, indicating greater risk-adjusted performance.

Impact of ESG Disclosures on Decision-Making

To investigate the association between ESG disclosure levels and wise investing choices, a correlation study was carried out.

Interpretation: Transparency in ESG reporting is crucial, as evidenced by the significant positive correlation found between the percentage of successful investment decisions and the degree of ESG disclosure.

Market Trends and Growth Prospects

An examination of the patterns in the development of sustainable investment assets in the last few years was done.

Interpretation: According to the data, sustainable investment assets increased steadily between 2019 and 2023 at varying growth rates, reaching a peak of 15% in 2021 and then gradually dropping in the years that followed. Over the course of the observation period, this pattern shows a consistent but varying interest in sustainable investments.

Conclusion

This study emphasizes how important it is for investors to prioritize financial returns over moral considerations when making decisions about their investments. Generally speaking, sustainable portfolios perform better than traditional ones, especially in times of market volatility. Transparency is essential since investor decisions are significantly impacted by the degree of ESG disclosure. The market for sustainable investment is expected to expand in the future due to increasing investor awareness and governmental backing. These findings support the creation of more successful sustainable investment strategies by offering insightful information to investors, politicians, and financial professionals.

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Exchange Rate Volatility and Sectoral Stock Market Risk: An EGARCH Analysis of the Indian IT and Pharmaceutical Sectors

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Citation: Abraham, A., & Ninan, M.M., & Revathy, A.R. (2026). Exchange Rate Volatility and Sectoral Stock Market Risk: An EGARCH Analysis of the Indian IT and Pharmaceutical Sectors. *Indian Journal of Accounting*, 58(1), 73-86

ABSTRACT

The study examines the impact of exchange rate volatility on sectoral stock market performance in India, with specific reference to the Information Technology (IT) and pharmaceutical sectors. The study explores whether the exchange rate risk transmits through mean returns or volatility spillovers using daily data from January 2018 to December 2025. The study uses an extensive econometric structure comprising Ordinary Least Squares (OLS), Vector Autoregression (VAR), Granger causality tests, Impulse Response Functions (IRF), ARCH-LM diagnostics, and Exponential Generalized Autoregressive Conditional Heteroskedasticity (EGARCH) models. USD/INR and EUR/INR are the two currency exchange rates used for representing exchange rate movements and Nifty50 is used as a control variable for capturing broad market movements. The results reveal that the changes in exchange rate does not have a significant influence on mean returns in either IT or Pharmaceutical sector. However, exchange rate volatility significantly affects conditional variance in both sectors, indicating strong volatility spillover effects. A stronger leverage effect can be seen in IT sector, whereas in pharmaceutical sector there is greater volatility persistence. The results implies that exchange rate risk in export-oriented sectors is demonstrated more through risk transmission than through changes in return. The study enriches the existing literature by adding varied dimensions to currency risk hedging portfolio management and financial regulation in emerging markets..

Keywords

Exchange rate volatility; Nifty IT; Nifty Pharma; Sectoral stock returns; Emerging markets; Currency risk; Volatility spillover; Asymmetric effects

Introduction

In today's highly integrated world financial system, the volatility of exchange rates has emerged as one of the most significant factors behind financial market uncertainty, especially in emerging countries like India. Exchange rates affect the competitiveness of exports, cost of imports, flow of foreign investments, and the bottom line of corporations, and hence affect the performance of equity markets. Therefore, the linkage between exchange rate variability and stock returns has gained a great deal of importance in international finance. Nevertheless, after years of

academic research, there still exists a lack of clarity as to whether such linkages exist through return or risk channels.

The Indian economy offers a useful backdrop against which exchange rate exposures can be studied, considering that India's economic integration into international business and finance is growing. The foreign exchange market in India has been through many changes since it adopted a floating exchange rate system in 1993, and the country's greater involvement in international value chains has ensured that there is greater

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impact of currency shocks on the Indian financial markets. The IT and pharmaceutical industries in India make up two sectors that could prove to be useful when comparing how exchange rate changes affect their operations and performance. Both of these industries are characterized by strong export orientation; however, the two industries are vastly different in terms of cost structures, imports, and the way they operate. While the IT sector receives its revenues in foreign currency and incurs its costs in domestic currency, the pharmaceutical industry is characterized by greater import content.

Literature review has produced varied findings about the association between the exchange rate and stock market relationship. While some researchers have found exchange rates to have a considerable effect on stock prices, others have found no such effect or very little impact. One shortcoming associated with previous research on this subject is that it has tended to look only at the direction of impact and ignored the volatility transmission part. There is a scarcity of literature dealing with the exchange rate impact on sectoral level in the case of India, specifically the export-oriented industries with varying structures.

This current research seeks to contribute to filling these gaps through analyzing the nature of foreign exchange rate exposure in the IT and Pharmaceutical sectors of India in terms of whether exchange rate exposure in Indian sectorial indices emerges from mean return effects or volatility effects. This paper makes several contributions to the existing literature in this regard. Firstly, there is a comparison between the IT and Pharmaceutical sectors in India, since both of these sectors are characterized by different types of business models in the context of export-oriented sectors. Secondly, instead of relying on USD/INR, the model includes both USD/INR and EUR/INR exchange rates since Europe is one of the largest markets for both industries. Lastly, the impact of general market performance is controlled using the Nifty 50 Index.

Theoretical Framework

The correlation between exchange rate changes and stock market returns is usually examined under one of two alternative theoretical perspectives: the flow perspective and the stock perspective. Both offer unique causality directions and implications for empirical examination.

The Flow-Oriented Model: The flow-oriented

approach, developed by Dornbusch and Fischer (1980), postulates that changes in exchange rates impact the international competitiveness of the companies and therefore their profitability and stock price. A weaker national currency would be beneficial for those firms engaged in exporting since it raises the domestic value of their foreign earnings, whereas a stronger currency could decrease their competitive advantages on the export market. This approach suggests the cause-effect relationship between exchange rates and stock prices, implying that the change in exchange rates should lead to the change in stock prices. In this case, the link between the two variables is based on international trade flows: the depreciation of the domestic currency makes exports more competitive and imports less competitive; thus, a better trade balance leads to an increase in the stock price of the exporting company.

Aggarwal (1981) was one of the first researchers who examined the relationship between the two variables empirically. He argued that currency movements have an effect on cash flows and competitiveness of the firms. Subsequent research by Jorion (1990) demonstrated that exchange rate exposure varies significantly across industries and firms depending on export orientation and foreign currency liabilities.

The Stock-Oriented Model: Another way to explain how changes in capital flow affect exchange rates is offered by the portfolio balance approach, attributed to Branson (1977) and Frankel (1983). According to this theory, changes in stock markets cause changes in capital flows that in turn cause exchange rate fluctuations. The process works through portfolio reallocation abroad. When stock markets show good performance, the amount of investment abroad is increased, thereby increasing the need for a nation's currency.

The International Capital Asset Pricing Model (ICAPM): ICAPM (Integrating CAPM and Currency Risk) was proposed by Solnik (1974) and subsequently refined by Adler & Dumas (1983). ICAPM provides another extension to the standard asset pricing model by considering currency risk as an additional systematic risk factor. With capital markets integrated globally, the investor will be exposed to both market risks as well as currency risks because changes in the exchange rates have a direct impact on the real return earned from international investments. According to the

ICAPM, investors need to earn risk premiums for undertaking exchange risk. Sercu (1980) went a step ahead by establishing that deviations from purchasing power parity constitute other sources of systematic risk for investors diversifying their portfolios internationally.

Asymmetric Volatility Theory: Asymmetric volatility effect theory has been based on work by Black (1976) and Christie (1982). These two proposed that there is a greater tendency for negative surprises to increase financial leverage and uncertainties compared to positive ones. There was the leverage effect since fall in stock prices would lead to an increase in the debt/equity ratios, hence, making the company risky and thus higher volatility. Other alternative reasons are volatility feedback effect, which holds that expectations of increased volatility will lead to higher required returns and lower prices, hence, there is a negative relationship between returns and volatility. Nelson (1991) modelled this with EGARCH to allow for study of asymmetric volatility transmission empirically. In the case of foreign exchange rates, a negative shock (depreciation) might cause greater volatility than positive shock due to various reasons.

Research in developed markets has also documented significant currency exposure effects. Bodnar and Gentry (1993) found substantial industry level exchange rate sensitivity in Canada, Japan and the United States. Griffin and Stulz (1997) argued that exchange rate shocks affect multinational firms differently depending on the global structure of production and competition.

Literature Review

Mean Return versus Volatility Effects

An increasing number of researchers have pointed out that exchange rate exposure can behave differently in mean returns and volatility transmission. The importance of this difference is important, since the absence of mean return effects does not necessarily indicate the absence of foreign exchange risk. The volatility spillover hypothesis (Bollerslev, 1986; Engle, 1982) suggests that large shocks in one market transmit to another, increasing conditional variance. Previous research mainly concentrated on the directional return effect trying to find out whether the stock price goes up or down in response to changes in exchange rate. More recent research, however, points out that exchange rate changes can influence uncertainty or market

risk without affecting mean returns.

According to Ajayi and Mougoue (1996), exchange rate shocks affect the stock market differently in the short term and in the long term, which implies that volatility transmission may be more persistent than the directional return effect. In addition, Kanas (2000) showed a large number of volatility spillovers from stock returns to exchange rate, and vice versa, in the case of leading industrial nations by means of the bivariate GARCH models. It was shown that the volatility spillover effect was bidirectional and asymmetric.

Dash and Madhava (2008) examined USD/INR fluctuations on Indian IT firms from 2005 to 2007, finding significant impact only on small-cap IT companies. Large and mid-cap firms were moderately affected. Abdalla Suliman (2017) studied Sudan's Khartoum stock exchange (2008-2011) and found that yesterday's exchange rate predicts today's stock returns with volatility spillovers from forex to equity markets.

Within the Indian economy, the latest literature has seen an increasing emphasis on volatility transmission. In their work, Mohapatra et al. (2024) found evidence of strong volatility spillovers due to changes in exchange rates in the Indian sectoral indices with the use of GARCH-based models. The time range considered by these authors was 2010 to 2022, and it was established that the most affected sectors were IT and pharmaceuticals. Likewise, Bhat et al. (2023) found that there were persistent effects of volatility transmission in Indian sectoral markets post-COVID, highlighting that the impact of volatility was intensified due to the effect of the pandemic.

Another interesting observation made in studies using asymmetric GARCH models is the finding that downside risks create bigger volatility response than upside risks. As per Phylaktis and Ravazzolo (2005), the impact of exchange rates on markets depended a lot on how financially integrated the markets were. Specifically, the authors pointed out that in emerging economies with substantial foreign investments, exchange rates could create higher impacts on financial markets because investors would react differently to exchange rates.

All these studies together point towards the inadequacy of conventional return models for measuring exchange rate exposures. Volatility models have to be used to account for such effects

which are asymmetrical and persistent in nature. This study contributes to the literature by directly examining the existence of volatility spillovers between exchange rates and sectoral returns even in the absence of any mean return effects.

Sectoral Heterogeneity in Emerging Markets

However, sector-level response to exchange rate movements will vary based on the level of export, import orientation, and structural differences. It is therefore important to comprehend this variance to effectively manage risks and implement policies to counter them.

IT Sector: In the IT sector of India, the bulk of the revenue comes from overseas clients, especially clients from USA and Europe. Large IT companies like Tata Consultancy Services (TCS), Infosys, and Wipro earn more than 80% of revenue in foreign currencies. As most of the revenue is in foreign currencies, but cost of operations (mainly salary costs) is incurred domestically, devaluation of the Indian rupee will be favorable for the sector. This results in a positive correlation between USD/INR exchange rate and IT stock returns. Nevertheless, the sector is also vulnerable to demand side pressures due to the direct link between currency and global economic conditions. Krishnamurthy et al. (2017) studied 2011-2016 data and found that NIFTY IT returns granger cause exchange rates, consistent with the stock-oriented model.

Pharmaceutical Sector: In India, the pharmaceutical sector has a somewhat complicated structure as well. In general, India is the world leader in generic drug exports to the United States; moreover, in the pharmaceutical sector, export sales make up a significant percentage of overall sales. On the other hand, the sector is highly dependent on the imports of APIs and raw materials from China. Therefore, an undervaluation of the exchange rate will cause production costs to increase. There may be additional risks such as the regulation of drug prices and quality control. Raza and Aravanan (2014) analyzed daily data from 2004 to 2012 finding no long-run causal relationship but short run bidirectional causality between exchange rates and stock markets. Hussain and Khan (2014) examined Pakistan's pharmaceutical sector (2003-2012) using cointegration and ECM, finding a significant long-run relationship between stock returns, exchange rates and market returns. Heidari et al. (2018) used a Markov-switching non-linear approach on Tehran stock exchange data (2005-2016) showing

that exchange rate varies across different economic regimes. Most directly, Ramya and Purushoth (2025) studies Indian pharmaceutical firms using correlation, regression and ANOVA concluding that exchange rate fluctuations significantly affect revenue, profitability and export earnings.

Comparison Across Sectors: According to Doidge et al. (2006), the globally oriented sectors have higher exchange rate exposure than domestic sectors. Likewise, Bartram and Karolyi (2006) argue that companies exporting more goods are more sensitive to exchange rates. The reason is that revenues earned in other currencies will have to be translated into the domestic currency. Nevertheless, hedges can be applied both operationally and financially to lower exposure.

In an Indian setting, the study conducted by Mohanty et al. (2023) revealed a strong interaction between exchange rates and sectoral stock indices, especially for export-based industries such as IT and energy. According to this study, there existed long-run relationships between exchange rates and sectoral indices despite the variation in direction of causality between the two variables. On the other hand, Chauhan et al. (2025) documented weak long-run effects of exchange rates on Indian sectoral stock indices. The contrast in the results of the studies shows the need for more than one methodology and the importance of differentiating between mean and variance effects. Shiva and Sethi (2015) found unidirectional causality from gold rates to exchange rates, not from exchange rates to stock markets. Ashiq and Shanmugham (2020) employed an autoregressive distributed lag model on 1999-2018 data finding significant long run effects on sectoral indices. Koradia et al. (2022) concluded that USD is the most influential currency with Nifty 50 negatively correlated with USD/INR. Kushwah and Negi (2024) confirmed that different sectors react differently with IT showing higher sensitivity than pharma.

The above structural differences point out that the exposure of the various sectors to exchange rates is heterogeneous and necessitates comparison. A blanket approach in managing exchange rate risks may prove ineffective owing to the distinct exposure faced by each industry.

Currency-Specific Exposure

Most of the previous literature is concentrated mainly on the analysis of USD-INR because of the

importance of the US dollar in the international business world. The US dollar plays a pivotal role in international business dealings, being the principal invoicing currency in international transactions, and emerging markets tend to pay much attention to their currencies' relationship with the dollar. At the same time, Europe can be considered a significant export destination for Indian companies, especially those dealing with IT and pharmaceuticals.

The latest study has highlighted the significance of currency basket strategies in emerging markets. According to Dominguez and Tesar (2006), firms face exposure to more than one currency and only considering exposure to the dollar can be understated in terms of the overall exchange rate risk exposure faced by a firm. This holds true especially for Indian IT and Pharma companies with diversification into different continents. Kumar and Maheswaran (2013) used GARCH models to examine volatility spillovers from crude oil and USD/INR to Indian industrial sectors, finding significant effects on energy and pharma sectors.

The Role of Market Control Variables

One critical aspect that needs to be taken care of while examining exchange rate exposure concerns incorporating the market control variables. There are several determinants other than exchange rate fluctuations that impact stock returns. These include market movements in general and interest rate differentials. Not controlling for market movements will result in biased estimates due to the omitted variable problem.

Nifty 50 index can serve as a proxy variable for the whole Indian stock market. Including Nifty 50 returns as a control variable will enable the current study to isolate sector-specific effects of exchange rates from market movements. The approach used here is in line with the decomposition of asset returns under the capital asset pricing model (CAPM). Under CAPM, asset returns are decomposed into two components: one related to the movement in the market and another associated with exchange rates.

The previous literature on exchange rate exposure without market correction can potentially overestimate the results in case of emerging markets due to the influence of similar external variables on the stock markets as well as the exchange rate. This is why the current research introduces a new variable called "Nifty 50" into the

OLS and EGARCH models as a means to control for the general market movements.

Research Gap

Even with considerable research on exchange rate exposure, there are still four major gaps in the literature.

Firstly, not much comparative analysis exists between the IT and Pharmaceutical industry in India. The majority of prior studies are either based on market indices or look at each sector individually. Comparative analysis is crucial because although both are export-based, their methods of exposure differ.

Secondly, most studies consider the USD/INR but overlook the effect of EUR/INR exposure, even though Europe plays a key role in the exports of India.

Thirdly, the literature does not differentiate between mean effect and volatility effect. Those who report insignificant mean effect tend to believe that exchange rate exposure is small, despite the presence of significant volatility spillovers.

Finally, very little literature incorporates OLS, VAR, IRF, and EGARCH into one single framework. It is important to understand how each methodology contributes towards understanding the relation between exchange rates and stock markets.

The current research attempts to rectify these weaknesses by positing that the effect of exchange rate exposure on export-based industries occurs mainly through volatility spillovers as opposed to direct return spillovers. The rationale behind this lies in the theory that although expected changes in exchange rates may be hedged by firms, any uncertainty related to this risk is uninsurable.

Hypotheses Development

Based on the theoretical framework and literature gaps, four hypotheses are formulated

H1: Sectoral and exchange rate returns exhibit non-normal, leptokurtic distributions, rejecting the null of normality.

H2: Exchange rate changes have no statistically significant immediate or lagged effect on IT and Pharma stock returns.

H3: There is a significant difference between IT and Pharma sectors in the magnitude and pattern of their response to USD/INR and EUR/INR shocks,

as measured by impulse response functions.

H4: Volatility in USD/INR and EUR/INR exchange rates has a statistically significant impact on the conditional variance of IT and Pharma sector returns.

Data and Methodology

Data Sources and Variables

The study uses daily closing prices data collected from the National Stock Exchange of India for the period January 1, 2018 to December 31, 2025. The variables used in the analysis are:

- Nifty IT Index Returns (R_IT)
- Nifty Pharma Index Returns (R_PHARMA)
- USD/INR Exchange Rate Returns (R_USD)
- EUR/INR Exchange Rate Returns (R_EUR)
- Nifty 50 Returns (R_NIFTY50)

Daily logarithmic returns are calculated using the following formula

$$R_t = \ln(P_t/P_{t-1})$$

Where

- R_t = return at time t
- P_t = current price
- P_{t-1} = previous period price

Stationarity Testing

The Augmented Dickey-Fuller test was applied to examine the stationarity properties of all return series. The null hypothesis of unit root was rejected for all variables at the 1% significance level.

Descriptive Statistics and Normality

Descriptive statistics and Jarque-Bera tests were conducted to examine distributional properties of the data. The results indicated excess kurtosis and non-normality across all return series, supporting the use of volatility-based econometric models.

Ordinary Least Squares (OLS) Model

To examine immediate exchange rate sensitivity in sectoral returns, the following regression models were estimated

IT Sector

$$R_{IT,t} = \alpha + \beta_1(R_{USD,t}) + \beta_2(R_{EUR,t}) + \beta_3(R_{N50,t}) + \epsilon_t$$

Pharmaceutical Sector

$$R_{PH,t} = \alpha + \beta_1(R_{USD,t}) + \beta_2(R_{EUR,t}) + \beta_3(R_{N50,t}) + \epsilon_t$$

Lagged Effects-VAR and Granger Causality

A Vector Autoregression (VAR) model with optimal lag length p determined by Akaike Information Criterion (AIC) was estimated. The general form

$$Y_t = c + \sum_{j=1}^p A_j Y_{t-j} + \epsilon_t$$

Where $Y_t = [R_{IT,t}, R_{USD,t}, R_{EUR,t}, R_{N50,t}]'$ for IT analysis. Then block exogeneity Wald tests (Granger Causality) was performed to determine whether past exchange rate returns predict current sectoral returns.

Dynamic Response Comparison- Impulse Response Function (IRF)

A one-standard-deviation shock to UD/INR AND EUR/INR was applied separately and the response of IT and pharma returns over a 10-day horizon was traced. Statistical significance was assessed using 95% confidence intervals.

Volatility Spillover-EGARCH (1,1)

The EGARCH model captures asymmetric volatility and includes exchange rate returns as exogenous variables in the variance equation:

$$\ln(\sigma_t^2) = \omega + \beta \ln \sigma_{t-1}^2 + \gamma \frac{u_{t-1}}{\sqrt{\sigma_{t-1}^2}} + \alpha \frac{u_{t-1}}{\sqrt{\sigma_{t-1}^2}} - \sqrt{\frac{2}{\pi}}$$

Where,

intercept term ω = ARCH coefficient γ = asymmetry coefficient

β = GARCH term = conditional variance at time t
 u_{t-1}^2 = lagged squares of error term = conditional variance of lagged term

Results

Descriptive Statistics and Normality

The following table helps to analyse the various statistical indicators in respect of returns.

The mean returns for all series are close to zero, ranging from 0.00015 (EUR/INR) to 0.00057 (IT sector), indicating daily returns are near zero on average. Median returns for IT, Pharma and EUR/INR are exactly zero, suggesting many days with no change. The standard deviation is highest for EUR/INR (0.01508) and IT sector (0.01351), indicating these are the most volatile series. Skewness is negative for most series except USD/INR (positive 0.104), indicating left-tail asymmetry-large

negative returns are more frequent than large positive returns for Nifty 50, IT, Pharma and EUR/INR. Kurtosis values are substantially above 3 (ranging from 9 to 32), confirming leptokurtic distribution (fat tails). The Jarque-Bera test rejects normality for all series at $P < 0.01$. Therefore, H1 is supported-returns are non-normal.

Stationarity-Augmented Dickey-Fuller (ADF) Test

The results from the Augmented Dickey Fuller (ADF) test indicate that Nifty fifty returns, IT returns, Pharma returns, USD INR and EURO INR are stationary as the null hypothesis of a unit root is rejected. Stationarity is a pre requisite for VAR and GARCH modelling and the results confirm that no differencing is required beyond the log-return transformation already applied.

Mean-Return Sensitivity-Ordinary Least Squares (OLS)

For the IT sector, the coefficient of Nifty 50 (market return) is positive (0.815) and highly significant ($p < 0.01$), indicating that IT sector returns strongly co-move with the broader market. In contrast, both USD/INR ($p = 0.826$) and EUR/INR ($p = 0.290$) are statistically insignificant. This means there is no immediate exchange rate sensitivity in IT sector mean returns. The R^2 of 40.2% suggests that market return explains a substantial portion of IT return variation, while exchange rates add no explanatory power. The F-statistic is significant, confirming the overall model is useful primarily due to the market return variable.

For the pharma sector, the market return

Table 1: Descriptive Statistics of Returns

	R_NIFTY50	R_IT	R_PHARMA	R_USD_INR	R_EUR_INR
Mean	0.00044	0.000569	0.000412	0.000165	0.000154
Median	0.000207	0	0	0.000119	0.00016
Maximum	0.084003	0.086404	0.09865	0.086754	0.123009
Minimum	-0.139038	-0.10065	-0.093507	-0.088205	-0.116973
Std. Dev.	0.010512	0.013509	0.011809	0.00983	0.015081
Skewness	-1.522207	-0.340402	-0.007295	0.103587	-0.032257
Kurtosis	26.88805	9.010618	9.564131	31.72709	27.57221

Source: Test Result

Table 2: Augmented Dickey-Fuller Test Results

Series	t-statistic	p-value	Decision
R_NIFTY50	-47.36036	0.0001	Stationary
R_IT	-46.24590	0.0001	Stationary
R_Pharma	-45.06963	0.0001	Stationary
R_USD_INR	-26.35054	0.0000	Stationary
R_EUR_INR	-26.03134	0.0000	Stationary

Source: Test Result

Table 3: OLS results -IT sector

Variable	Coefficient	Std. Error	t-Statistic	P-value
Constant	0.000206	0.000229	0.901	0.368
R_USD_INR	0.005407	0.024664	0.219	0.826
R_EUR_INR	0.016925	0.016002	1.0578	0.290
R_NIFTY50	0.815435	0.021904	37.228	0.000

$R^2 = 0.402$; Adj. $R^2 = 0.401$; $F = 465.9$ ($p = 0.000$) Source: Test Result

Table 4: OLS results- Pharma sector

Variable	Coefficient	Std. Error	t-Statistic	P-value
Constant	0.000145	0.000218	0.666	0.506
R_USD_INR	0.009569	0.023459	0.408	0.683
R_EUR_INR	-0.01021	0.015219	-0.671	0.502
R_NIFTY50	0.606824	0.020833	29.128	0.000

$R^2 = 0.292$; Adj. $R^2 = 0.291$; $F = 285.9$ ($p = 0.000$) Source: Test Result

coefficient is (0.607) is again positive and highly significant ($p < 0.01$), confirming that Pharma also follows broader market trends. However, USD/INR ($p = 0.683$) and EUR/INR ($p = 0.502$) are statistically insignificant with coefficients close to zero. The EUR/INR coefficient is negative (-0.010) suggesting a weak negative relationship, but it is not statistically different from zero. The R^2 (29.2%) is lower than for IT, indicating that market return and exchange rates collectively explain less of Pharma's variation—other sector-specific factors (regulatory news, patent expirations, drug approvals) likely play a larger role. Based on tables 3 and 4, it is found that there is no immediate exchange rate sensitivity in mean returns for either sector.

The VAR model with 6 lags was estimated separately for IT and Pharma. The Granger causality test examines whether past values of exchange rate returns (1-day to 6-day lags) collectively help predict current sectoral returns. For the IT sector, USD/INR ($p = 0.708$) and EUR/INR ($p = 0.312$)

both have p -values > 0.05 , inferring that the null of no granger causality is not rejected. For the Pharma sector, USD/INR ($p = 0.454$) and EUR/INR ($p = 0.160$) are also insignificant. Combined with the OLS results, it can be concluded that there is no exchange rate sensitivity in mean returns—neither contemporaneous nor lagged. Therefore, H2 is not rejected.

Comparative Effect-Impulse Response Functions (IRF)

In models like Vector Autoregression (VAR), an IRF shows how a one-time “shock,” or sudden change, in one variable affects itself and other variables in the system. The X-axis represents time, measured in periods, months, or years, after the initial shock. The Y-axis shows the size and direction of the response in the affected variable. The plot indicates whether the shock's effect is temporary, fading over time, or permanent, and whether the reaction happens right away or is delayed.

Lagged Effects- VAR and Granger Causality

Table 5: Granger Causality Test Results (VAR-Block Exogeneity Wald Test)

Dependent Variable	Excluded Variable	Chi-Square	df	p-value	Decision
R_IT	R_USD_INR	3.770	6	0.708	No Granger Causality
R_IT	R_EUR_INR	7.100	6	0.312	No Granger Causality
R_PHARMA	R_USD_INR	5.732	6	0.454	No Granger Causality
R_PHARMA	R_EUR_INR	9.258	6	0.160	No Granger Causality

Source: Test Result

Figure 1: Response of IT Returns to a One Standard Deviation Shock in USD/INR

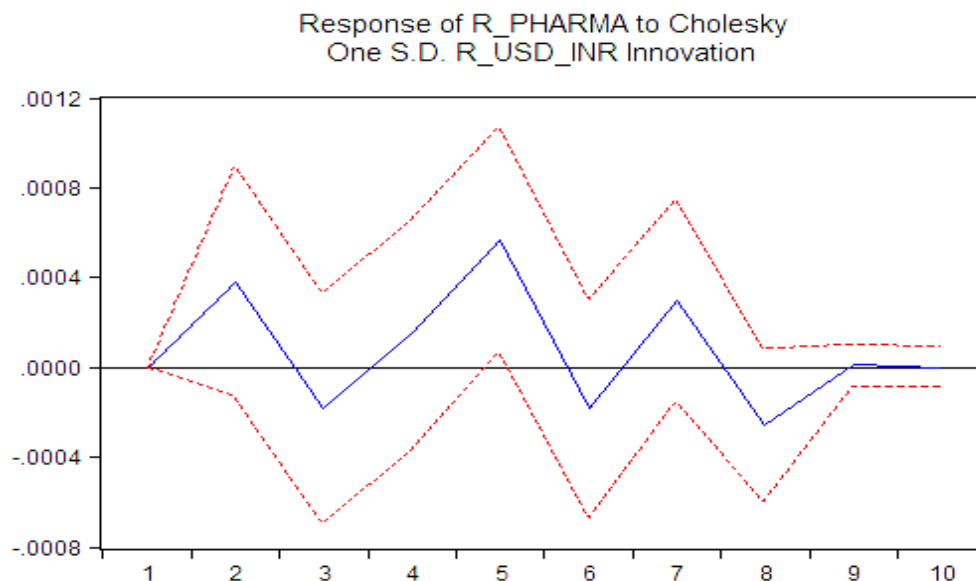


Figure 2: Response of Pharma Returns to a One Standard Deviation Shock in USD/INR

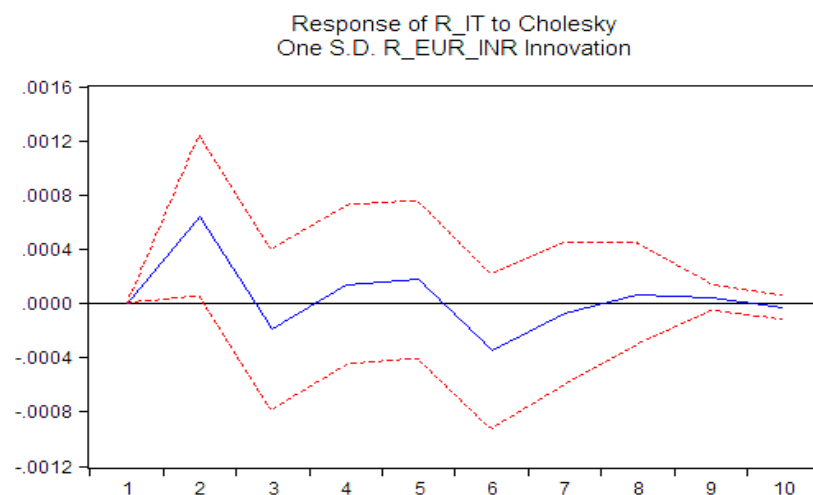


Figure 3: Response of IT Returns to a One Standard Deviation Shock in EUR/INR

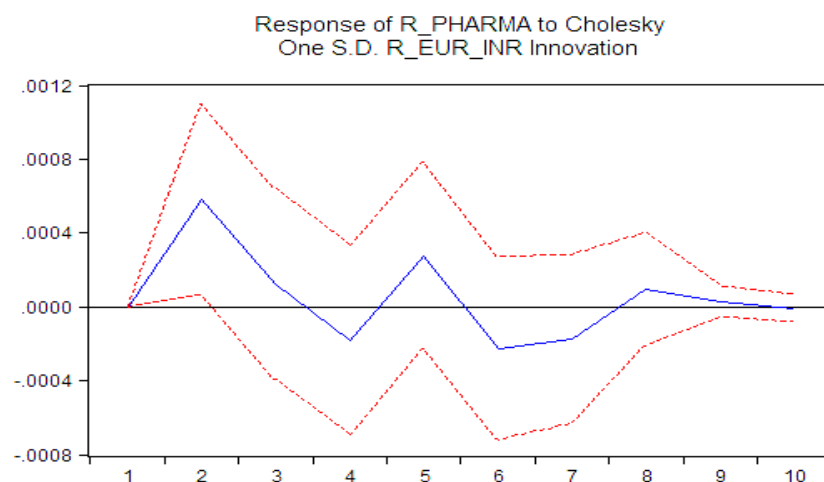
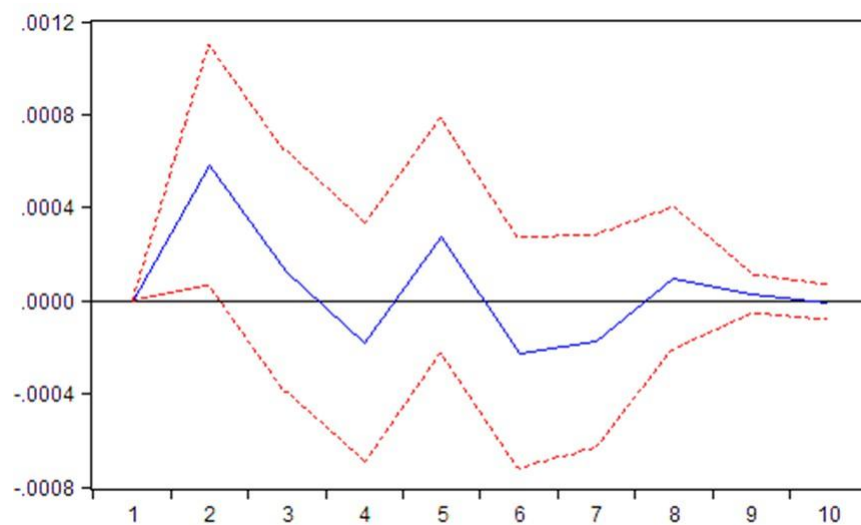


Figure 4: Response of Pharma Returns to a One Standard Deviation Shock in EUR/INR



A positive shock to USD/INR (rupee depreciation against the dollar) generates a positive response in IT sector returns, consistent with the export-oriented nature of the sector. The response is immediate, peaking around period 5 (approximately 0.00045) and gradually returns to baseline by period 9-10. The lower bound of the 95% confidence interval remains above zero during the peak, indicating statistical significance. The effect is transitory- no permanent impact on return levels.

Pharma sector also responds positively to USD/INR depreciation, but the peak magnitude (0.0006) is higher than IT's peak (0.00045). The confidence intervals are noticeably wider, indicating greater uncertainty in Pharma's response. The effect remains transitory, fading by period 10. Comparing Figure 1 and Figure 2, Pharma exhibits a higher magnitude but less precise response. Since the magnitude, shape and confidence band width differ, H3 is supported for USD/INR- there is a significant difference between IT and Pharma in response to USD shocks.

A positive shock to EUR/INR (rupee depreciation against the euro) generates a small positive response in IT returns, peaking at period 2.

However, the lower bound of the 95% confidence interval is very close to zero, and by period 3, the confidence interval straddles zero, indicating the effect is barely significant or insignificant. The response magnitude is smaller than for USD/INR.

Pharma's response to EUR/INR follows a similar pattern to IT, with a small peak at period 2. The confidence intervals are wider than IT's indicating more noise but the overall pattern and magnitude are not statistically distinguishable from IT's response. Therefore, for EUR/INR, H3 is not supported- there is no significant difference between IT and Pharma in response to euro shocks.

6.6 Volatility Spillover-ARCH-LM and EGARCH

The ARCH-LM test checks for autoregressive conditional heteroskedasticity. For both sectors, the p-value is less than 0.05. hence the null hypothesis of no ARCH effect is rejected. This confirms that volatility clustering is present in both sector returns, justifying the use of an EGARCH model rather than a simple homoscedastic model.

Volatility persistence (β): The GARCH coefficient β is highly significant ($p < 0.01$) for both sectors, confirming that volatility shocks persist over

Table 6: ARCH-LM Test for ARCH Effects

Sector	Test Statistic	p-value
IT	10.953	0.0009
Pharma	84.035	0.0000

Source: Test Result

Table 7: EGARCH (1,1) Results with Exogenous Exchange Rate Returns

Coefficients	IT Sector		Pharma sector	
	Z statistic	p-value	Z statistic	p-value
Omega (ω)	-7.121***	0.0000	-5.810***	0.0000
Alpha (α)-ARCH	7.618***	0.000.0	8.785***	0.0000
Gamma (γ)-Asymmetry	-3.854***	0.0001	-1.818*	0.0691
Beta (β)-GARCH	41.275***	0.0000	392.852**	0.0000
USD/INR (δ_1)	7.821***	0.0000	8.891***	0.0000
EUR/INR (δ_2)	6.287***	0.0000	2.232**	0.0256

Source: Test Result; *, **, *** indicate significance at 10%, 5%, 1% levels respectively

Table 8: Summary of Hypothesis Testing

Hypothesis	Description	Result
H1	Returns are non-normal	Supported (Table 1)
H2	No exchange rate sensitivity in mean returns	Not rejected (Tables 3,4,5)
H3 (USD/INR)	Significant difference between IT and pharma	Supported (Figures1,2)
H3 (EUR/INR)	Significant difference between IT and pharma	Not Supported (Figures3,4)
H4	Exchange rate volatility affects sectoral variance	Supported (Table 7)

Source: Authors compilation

time. pharma's β (392.852) is substantially larger than IT's (41.275) indicating that shocks to pharma volatility decay much more slowly- volatility remains elevated for longer periods in the pharma sector.

Leverage effect (γ): For the IT sector, γ is negative (-3.854) and statistically significant at 1%. This means bad news (negative shocks) increases volatility more than good news (positive shocks)- a classic leverage effect. For pharma, γ is also negative but only significant at 10%. This indicates a weaker and less reliable asymmetry in pharma.

Volatility spillover (δ_1, δ_2): Both USD/INR and EUR/INR coefficients are positive and statistically significant for both sectors ($p < 0.05$ for all, except EUR/INR in pharma at $p < 0.05$). This means that exchange rate volatility directly increases the conditional variance of sectoral returns. The effect is stronger for USD/INR (coefficients 7.82-8.89) then for EUR/INR (2.23-6.29). Therefore, H4 is supported- exchange rate volatility has a significant impact on the volatility of IT and pharma stock returns.

Discussion

Why no Mean Sensitivity but Strong Volatility Spillover?

The absence of mean exchange rate sensitivity (H2 not rejected) despite strong volatility spillover (H4 supported) is an important finding. There are several explanations for the same:

First hedging practices: Large Indian IT and pharma firms actively use forward contracts, options and natural hedges (matching foreign currency revenues with expenses). This eliminates the mean impact but cannot eliminate variance- unexpected volatility still affects risk perception and option pricing.

Second, market efficiency: In an efficient market, anticipated exchange rate changes are quickly priced in. Only unanticipated volatility (shocks) affects stock return variance without affecting mean returns.

Third, pharma's dual structure: The offsetting effects of export revenue gain and import cost increase cancel out in mean but increase variance, consistent with the IRF finding of higher magnitude but noisier response.

Asymmetric Volatility (Leverage Effect)

The significant negative γ for IT indicates that a

negative currency shock increases IT sector volatility more than a positive shock of equal magnitude. This is rational as rupee appreciation directly reduces the INR value of dollar/euro revenues, creating negative earnings surprises. Investors overreact to bad news relative to good news consistent with behavioral finance (loss aversion).

Pharma's weaker asymmetry (γ only 10% significant) suggests that the import cost offset partially cushions negative currency shocks, making the sector less prone to asymmetric volatility.

USD vs. EUR Dominance

USD/INR shocks consistently produce stronger responses than EUR/INR in both IRF and EGARCH. This reflects trade composition: the US accounts for approximately 60% of Indian IT exports and 30-35% of pharma exports, while Europe accounts for 20-25%. Hedging strategies should prioritise USD.

Comparison with Prior Literature

The study's finding of no mean sensitivity aligns with Chauhan et al. (2025) but contrasts with Ashiq and Shanmugham (2020) and Mohapatra et al. (2024). The difference likely stems from (a) period- the study period is 2018-2025 which includes post COVID structural changes; (b) return frequency- daily vs monthly; (c) control for Nifty 50 (market return) which absorbs some explanatory power.

The EGARCH volatility spillover results strongly support Mohapatra et al. (2024) and Bhat et al. (2023) confirming that exchange rate uncertainty is a priced risk factor even when mean effects are absent.

Conclusion and Implications

Summary of Findings

The study examined the impact of exchange rate volatility on Indian IT and Pharmaceutical sector stock returns from 2018 to 2025. Using ADF, OLS, VAR-Granger, IRF and EGARCH, it was found that

- Returns are non-normal, leptokurtic and stationary.
- No immediate or lagged exchange rate sensitivity in mean returns (H2 not rejected).
- Significant difference in response to USD/INR shocks (pharma higher magnitude, more volatile), but no difference for EUR/INR (H3 partially supported).
- Strong volatility spillovers from both USD/INR

and EUR/INR (H4 supported).

- IT sector exhibits significant leverage effect (asymmetric volatility); pharma shows weaker asymmetry.

Theoretical Contributions

The study makes three theoretical contributions. First, it demonstrates that exchange rate exposure can be purely second-moment (volatility) without first-moment (mean) effects- a distinction often overlooked. Second, it shows that leverage effects are sector-specific, depending on cost structure and supply chain integration. Third, it confirms that USD dominates EUR in transmitting currency risk to Indian sectors.

These contributions extend the theoretical literature by suggesting that models of exchange rate exposure should include both a mean equation (predictable effects) and a variance equation (risk effects). The finding that asymmetry varies by sector suggests that aggregate market-level leverage effects may mask important heterogeneity.

Managerial Implications

For investors: Hedge USD exposure more aggressively than EUR exposure. Pharma stocks require tighter stop-losses during currency turbulence due to higher magnitude responses. IT stocks require asymmetric risk management- negative currency news disproportionately increases volatility.

For portfolio managers: Include exchange rate volatility as a separate risk factor in sectoral allocation models, not just in mean returns. Consider pairing IT (high leverage effect) with pharma (high magnitude, low persistence) for diversification within export-oriented portfolios.

For policy makers: Enhance the depth of INR derivatives markets (forwards, options, swaps) to help firms manage short term currency volatility. Consider sector specific forex facilities for pharma due to dual export-import exposure.

Limitations and Future Research

Three limitations warrant acknowledgement.

First, we used only two exchange rates (USD/INR, EUR/INR); further studies could include GBP/INR, JPY/INR and CNY/INR as these currencies are increasingly important for Indian trade.

Second, the period (8 years) is relatively short for

long-run cointegration tests; a 20-year study would complement our findings by testing whether mean sensitivity has changed over time.

Third, we did not separately analyse COVID and post-COVID sub periods; further research could use regime switching models (Markov-switching GARCH) to test for structural breaks.

Methodologically, further studies could apply machine learning (LASSO-VAR, Bayesian GARCH, neural network volatility models) to capture non-linearities. Additionally, firm level analysis (instead of sectoral indices) could identify which specific companies are most vulnerable to currency volatility.

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Financial Performance Assessment of Selected Indian Paper Industries: Evidence from Panel Data and TOPSIS Analysis

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Citation: Shah, B., & Kaur, S. (2026). Financial Performance Assessment of Selected Indian Paper Industries: Evidence from Panel Data and TOPSIS Analysis. *Indian Journal of Accounting*, 58(1), 87-106

ABSTRACT

The study aims to evaluate the financial performance of selected paper industries and examine the profitability, capital and operational efficiency from 2015-16 to 2024-25. The present study has employed secondary data on the three paper industries, namely Orient Paper & Industries Ltd., Kuantum Papers Ltd., and Pudumjee Paper Products Ltd., derived from the CMIE's PROWESS database. A set of financial ratios has been used to calculate efficiency and profitability, whereas panel analysis and comparison-based tests have been utilised to estimate relationships among the variables. Additionally, trend assessment and the TOPSIS method are used to measure temporal patterns and overall comparative performance. The results show significant differences in return on capital employed and net profit ratio across the selected industries. Firstly, total asset turnover is positively related to return on capital employed, whereas operating ratio is negatively related to it. Based on the TOPSIS ranking, Kuantum displays the best overall performance, followed by Pudumjee and Orient. Pudumjee shows uniform progress over the period, while Orient shows considerable fluctuations. The study presents an analysis of selected paper industries over a 10-year period, incorporating ratios, panel-based assessment, temporal patterns, and a multi-criteria decision framework to evaluate performance. .

Keywords

Paper industry, Orient, Kuantum, Pudumjee, PROWESS

Introduction

The Indian paper industry plays an important role in manufacturing paper and paper-based products for various services, such as supplying products for hygiene, printing, and packaging, as well as other purposes. The increasing demand for a variety of paper products has created significant opportunities for the Indian paper sector. Deshwal et al. (2019). However, the performance of the paper industry remains closely linked to its ability to manage operating costs, employ assets efficiently, and generate higher returns on capital employed. Hence, estimating financial performance through profitability and efficiency indicators is viable for comprehending the financial stability of industries.

Financial performance can be assessed through various accounting indicators. Ratio analysis provides an organised method for estimating profitability, efficiency, and other measures. Ratios have been used as an instrument to evaluate the financial viability of industries. (Horrigan, 1968; Suthar, 2018). Gross profit and net profit ratios indicate the industry's ability to generate revenue from total sales, whereas total asset turnover indicates the efficient utilisation of assets. The operating ratio reflects the percentage of sales consumed by operating costs, while return on capital employed reflects the total capital gained from the amount invested in a business by an industry. Therefore, these indicators provide a

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more extensive estimation of financial performance than relying on a single tool. Ratio analysis also aids stakeholders in decision-making by evaluating profitability and efficiency. Som and Goel (2021).

Previous studies have presented their findings on the financial performance of Indian paper industries using ratio analysis. For instance, Mahajan (2014) highlighted the significance of capital returns, while Yuvaraj and Kathirvel (2015) recognised variations in liquidity and profitability in the private sector. Saravanan and Devaki (2016) stated differences in financial and operational performance, whereas Podile (2018) emphasised the essentials of asset utilisation in a small-scale paper industry. Iniyavan (2019) reported variability in efficiency across industries. Ray (2011) and Sinha and Sucharitha (2022) assessed the financial viability of the paper industry using the ratio method.

Despite these contributions, there are significant gaps in the literature. Most of the studies focused on descriptive, ratio-based analyses with little emphasis on the association between assets and operating efficiency, and on return on capital employed, using panel data analysis. Moreover, research has been largely focused on large-scale industries, while little attention has been paid to small and medium-sized industries.

The selected period from 2015-16 to 2024-25 evaluates and observes the financial performance of selected paper industries across various economic conditions prevailing in the country. Consequently, the present study aims to estimate temporal patterns in financial viability over the selected period rather than attributing observed changes directly to COVID-19. This difference is primary, as the study does not assess the COVID-period model or conduct any causal evaluation of the pandemic's impact on financial performance.

Theoretical Framework

Resource-Based View

Wernerfelt (1984) provides the principal theoretical basis for the study. The theory explains that industries can achieve greater performance through effective management, capabilities, and the proper utilisation of internal resources rather than relying on external forces.

In this context, asset utilisation and capital employed are the two most important resources in the present study. These two can contribute to

consistent increases in sales and higher returns on invested capital. Therefore, a higher total asset turnover indicates productive utilisation of assets and is expected to positively influence return on capital.

Operational efficiency is another essential measure of organisational resources. The higher the ratio, the more revenue is absorbed by operating expenses, leaving less surplus or profit to generate a return on capital. Whereas a lower ratio results in improved financial performance.

Therefore, the resource-based view provides a theoretical foundation for explaining the association between internal resources and consistent financial performance. In the present study, TATR demonstrates efficiency in asset use, OR represents cost efficiency, and ROCE explains the returns or outcomes of capital invested. Hence, the theoretical basis rests on a positive relationship between TATR & ROCE and a negative relationship between OR & ROCE.

Conceptual Framework

Based on the resource-based view, the present study develops a conceptual framework that links asset utilisation and operational efficiency to financial performance. It further identifies total asset turnover and operating ratio as explanatory variables and return on capital employed as the dependent variable.

Asset utilisation (TATR) ➡ *positive relationship*
➡ with Return on capital employed (ROCE)

Operating efficiency (OR) ➡ *negative relationship*
➡ with Return on capital employed (ROCE)

The conceptual framework proposes that industries that utilise their assets more effectively are expected to generate higher returns on capital invested. In comparison, those with rising operating costs are expected to generate lower returns. Thus, the framework provides a basis for further empirical evaluation of TATR, OR, and ROCE in the selected paper industries.

Literature Review

The literature comprises papers from reputable journals that provide detailed information on the methodology used in this paper.

Theme 1: Ratio analysis and financial performance

Several studies have highlighted the significance of

the ratio method across disciplines such as commerce, management, economics, mathematics, and environmental studies. Horrigan (1968) predicted in his study that the ratio would be a noteworthy tool for assessing the soundness of an industry and an advantageous instrument for underdeveloped (UDCs) and developing countries. The investigation will be comprehensive, especially if conducted in small numbers or for internal management. At the same time, Nissim & Penman (2001) affirmed that ratio analysis is not just descriptive but a comprehensive forecasting method. In addition, the following studies have emphasised the assessment of the paper and manufacturing industries using ratio analysis to evaluate financial performance and to suggest capital efficiency and asset utilisation as key to enduring profitability.

Theme 2: Capital efficiency and panel data

There is a growing literature on the long-term efficient use of capital and on the evaluation of financial sustainability using panel data. Vataavu (2015) and Chadha and Sharma (2015) showed that industries rely on external sources for advances, which can lead to undesirable consequences. The best approach is to fund from internal reserves and maintain more equity than debt. The study showed that excessive borrowing harms returns, whereas efficient capital management improves performance. Similarly, Levicky et al. (2026) found that asset expansion and balanced working capital are important because they remain statistically stable across all model specifications.

Theme 3: TOPSIS and evaluating comparative performance

Multi-criteria decision-making techniques are actively adopted in the present studies to evaluate and rank firms based on their financial indicators. Behzadian et al. (2012) highlighted the importance of ranking methods, citing more than 400 articles across various disciplines. Therefore, the result confirmed that the method adopted with other tools gave optimal conclusions. Additionally, a study by Üçüncü et al. (2018) applied TOPSIS to rank paper industries and successfully identified strong and weak ones by incorporating solvency, profitability, and liquidity ratios.

Theme 4: Environmental sustainability and financial performance

The development of the paper industry plays a prominent role in economic growth; however,

paper production consumes significant amounts of resources, including water, chemicals, energy, and other scarce raw materials. The production and consumption of paper and paper-made products can be made sustainable and environmentally friendly; however, this requires careful attention and environmental consciousness. Wagner *et al.* (2002) studied the European paper industries. They concluded that while traditionalists believed environmental regulations could increase costs, Porter's hypothesis suggests they may spur smart innovation that yields profits. To relate environmental and financial indicators. Similarly, Spicer (1980) noted that pollution control earns the market's trust, which leads to better returns by gaining stakeholders' confidence and reducing risk. A recent study by Nguyen (2025), after conducting empirical tests, reported that environmentally friendly innovation may reduce returns on assets due to initial investment up to a threshold. However, beyond that, it will increase profitability in the long term. Studies by Singh et al. (2022), Mandeep et al. (2019), and Azevedo et al. (2019) highlighted the need to raise awareness of recycling, waste management, and the efficient utilisation of raw materials through sustainable environmental practices.

Theme 5: Analytical techniques and evaluation of financial performance

To strengthen ratio analysis, advanced tools are available alongside traditional methods to evaluate performance and identify long-term trends. Nanda et al. (2021) applied Tukey's HSD test and trend analysis to understand changes in financial variables over time and make sound decisions based on visible patterns. Similarly, Caloiero et al. (2018) highlighted in their study that trend analysis can complement ratio analysis in the effective estimation of financial performance by offering a useful perspective through its display of increasing and decreasing phases.

Theme 6: Indian paper industries and evaluation of financial performance

Several studies have calculated financial performance using ratio analysis. Mahajan (2014) examined the capital management of all paper mills in Pune, Maharashtra, and highlighted the significance of efficient capital utilisation. Yuvaraaj and Kathirvel (2015) conducted a study of private paper mills in India and found differences in liquidity and profitability across firms. Saravanan and

Devaki (2016) analysed the overall financial health of India's paper industry and found variations in operational performance that affected profitability. Podile (2018) analysed a small-scale firm and conducted a case study of 'Sri Ramachandra Paper Boards Limited,' situated in Hyderabad, and highlighted the importance of increasing assets and improving performance. Iniyavan (2019) conducted a comparative study of the Andhra Paper Company and the Tamil Nadu Newsprint Paper Company and observed major differences in efficiency indicators. Lastly, Sinha and Sucharitha (2022) conducted a general analysis of paper companies in India using various ratios and provided broad conclusions on the Indian paper industry. Therefore, these studies primarily relied on descriptive analyses and focused on large-scale industries, without implementing any comprehensive framework.

Research Gaps

The existing literature on financial performance concerning the paper industry has discovered substantial, important gaps.

First, most of the studies were published before the pandemic, and hence, there is limited evidence on the changes that occurred during the outbreak. Additionally, as no COVID model is introduced in this paper, the study treats pandemic years as a temporal factor to examine variations. It does not examine a causal connection between COVID and financial performance.

Second, prior studies have focused primarily on large-scale paper companies such as JK Paper Ltd., West Coast Paper Mills, and Tamil Nadu Newsprint and Papers Ltd. In contrast, smaller or medium-scale companies have received less attention. This created a significant gap in understanding the financial strength of all industries within a sector.

Third, the literature showed that many studies were descriptive in nature and did not capture the key determinants of profitability using panel data approaches. Moreover, previous studies often provided an overall picture of financial performance in India and failed to show industry-specific changes. This created a gap in narrowing industry-specific studies or comparative estimation.

Fourth, many earlier papers rely on private or limited databases or on a limited set of variables, which may lead to duplication or inaccurate results. The present study uses PROWESS, provided by the CMIE, an authentic government database

of financial information that includes all annual reports.

Fifth, most of the studies were conducted over short time periods or were cross-sectional and did not use a robust empirical framework, such as panel analysis, TOPSIS, or Tukey's test, for comparative valuation.

Sixth, to the best of my knowledge, there are very few studies that have jointly combined trend analysis, TOPSIS, multiple regression, a random-effects model and Tukey's HSD test in a single study to provide a comprehensive assessment of financial performance.

Therefore, the present study attempts to fill these gaps by writing a paper on comparative financial analysis for the long term (2015 to 2024-25) with the integration of ratio estimation, ANOVA, Tukey HSD, correlation, multiple regression, random-effect models, trend analysis, moving average method, and the TOPSIS framework.

Objectives of the study

1. To evaluate the financial performance of selected Indian paper industries during the period 2015-16 to 2024-25.
2. To determine whether significant differences exist in the financial performance of the selected Indian paper industries.
3. To examine the relationship between operational efficiency and financial performance among the selected Indian paper industries.
4. To analyse the temporal patterns in the financial performance of the selected Indian paper industries during the study period.
5. To assess the overall financial performance of the selected Indian paper industries.

Hypothesis of the study

H1

There is a significant difference in financial performance among the selected Indian paper industries.

H2

The total asset turnover ratio and operating ratio have a significant impact on return on capital employed among the selected Indian paper industries.

Research Methodology

Research Design

The present study has adopted a longitudinal,

quantitative research method to analyse the financial performance of selected Indian paper industries, using secondary data to examine changes in profitability levels from 2015-16 to 2024-25. Additionally, descriptive and inferential techniques, along with comparative and trend assessments, have been employed to detect variations in performance during the selected period.

Population and Sample Selection

To select specific industries, the CMIE-Prowess database has been used. The initial search generated 645 firms, which were used as the primary population for further screening of relevant industries. From this set of samples, 18 leading paper industries were taken based on net sales and earnings per share. These industries formed the preliminary opening for final selection. Furthermore, they were scrutinised for the availability and consistency of data. Industries for which the dataset was incomplete or insufficient for the duration of the study were omitted.

1. JK Paper Limited
2. Tamil Nadu Newsprint and Papers Limited
3. West Coast Paper Mills Limited
4. Emami Paper Mills Limited
5. Seshasayee Paper and Boards Limited
6. Andhra Paper Limited
7. Satia Industries Limited
8. um Papers Limited
9. Orient Paper & Industries Limited
10. Pudumjee Paper Products Limited

Of the 10 industries, Kuantum, Orient and Pudumjee Paper Industries were purposively selected for the present study. The final decision was based on inclusion and exclusion criteria.

Inclusion Criteria:

1. The industries that were classified as paper manufacturing units, and are registered in

the Prowess record, and recognised as core industrial units amongst the paper industry, were considered for the analysis.

2. The required data were obtainable for all the years covered in the study and encompass complete financial information on variables essential for further evaluation.
3. The financial information was presented in a manner that facilitated effective comparison among the three paper industries over the period.

Exclusion Criteria:

1. Industries outside the scope of paper manufacturing units, or not among the leading paper mills, were excluded from the study.
2. Financial information was unavailable for one or more of the years included in the study, and certain information required to calculate profitability was also unavailable.
3. Across several industries, differences in how financial information is presented affect data uniformity, thus limiting the scope for effective year-wise comparisons.

Lastly, Orient exhibited comparatively volatile and weak financial performance, carrying losses in recent years. In contrast, Pudumjee demonstrated relatively unswerving performance despite incurring losses in the initial period, while Kuantum displayed robust and vigorous financial performance. Hence, these contrasting cases of paper industries provided a suitable foundation for examining differences in profitability levels among the selected paper industries.

The analysis is based on secondary data accessed from the CMIE-Prowess database for the period 2015-16 to 2024-25. The financial records for the three industries were obtained from a single source to maintain data uniformity. The study incorporates

Table 1. Stages of Selection and Final Sample Formation

Stage	Selection/Sampling procedure	No. of companies
1	Initial industries identified through CMIE Prowess	645
2	Leading/relevant paper industries identified based on earnings per net sales	18
3	Industries retained after preliminary screening	10
4	Industries selected on the basis of inclusion & exclusion	3
<i>Final sample</i>	<i>Kuantum, Orient and Pudumjee</i>	<i>3</i>
Study observations	3 companies × 10 financial years	30

Data Sources

financial ratios including gross profit ratio, net profit ratio, total asset turnover ratio, operating ratio, and return on capital employed ratio.

Study Period

The ten-year period was used to evaluate financial performance over a long horizon and observe differences under the dynamic conditions prevailing in an economy. The present study does not calculate a separate COVID-19 model. Hence, all the variations observed during the pandemic are part of broader trends over the duration of the study rather than being considered causal effects of COVID-19.

The study employs descriptive statistics, one-way ANOVA to measure statistically significant differences in mean for the financial variables across three selected industries, Tukey's honest significant difference post hoc test to pinpoint particular pair of industries for which there is significant difference, correlation to estimate connections between financial variables, multiple regression to measure relationship between explanatory variable

and financial efficiency, random-effects model, trend analysis, moving-average pattern method, and, lastly, the technique for order of preference by similarity to ideal solution (TOPSIS).

The software used in the present study is Microsoft Excel for descriptive and trend analysis, ANOVA, correlation, regression, moving average, and TOPSIS. EViews for the fixed-effect model & MathType for writing equations.

One-Way ANOVA Results for Return on Capital Employed and Net Profit Ratio

As we can observe from the tables above, the average for the Kuantum and Pudumjee paper industries is far higher than that of the Orient Paper Industry, suggesting greater returns on capital. Moreover, the p-value is 0.000433, which is < 0.05 , so the null hypothesis is rejected. This leads to the acceptance of the alternative hypothesis, indicating a significant difference in the return on capital employed ratio among the selected paper industries. Comparatively, Orient's lower ROCE is related to variations in profits, operational management, and

Table 2: Summary of variables

Variables		Calculations
GPR	Gross profit ratio	Gross profit/net sales * 100
NPR	Net profit ratio	Net profit/net sales*100
TATR	Total assets turnover ratio	Net sales/total assets
OR	Operating ratio	Cost of goods sold + operating expenses/net sales *100
ROCE	Return on capital employed ratio	Earnings before interest & tax (EBIT)/capital employed*100
Capital employed	---	Total assets-current liabilities
TREND	---	Current year/base year * 100. (Base year 2015-16)

Statistical Techniques

Table 3: Summary Statistics for ROCE Among Selected Paper Industries

Groups	Count	Average	Variance
Orient	10	3.351	25.147
Kuantum	10	10.386	34.605
Pudumjee	10	13.84	22.208

Source: Author's calculations

Table 4. Analysis of Variance (ANOVA) Results for ROCE Among Selected Paper Industries

Source of Variation	SS	df	MS	F	P-value	F crit
Between Groups	571.4682	2	285.734	10.459	0.000433	3.354
Within Groups	737.6405	27	27.320	---	---	---
Total	1309.109	29	---	---	---	---

Source: Author's calculations

the non-optimal use of capital. Hence, the results suggest that the selected industries differ in their average ROCE over the period.

Tukey's Honest Significant Difference (HSD)

$$HSD = 3.506 \cdot \sqrt{\frac{27.320}{10}} = 5.79$$

Where q = range value.

MSW = Mean square groups from ANOVA.

n = No. of observations per industry

$$HSD = q \cdot \sqrt{\frac{MSW}{n}} \quad MS_{Within} = \frac{SS_{Within}}{df_{Within}}$$

$$MS_{Within} = \frac{737.641}{27} = 27.320$$

Mean Difference in Tukey Test

Mean Difference = Mean of Industry A - Mean of Industry B

The Tukey post hoc test was conducted immediately after ANOVA to determine which specific industries differ significantly in ROCE. The studentized range value is q = 3.506, taken from the Tukey HSD table for 3 groups/industries at the 5% significance level, with degrees of freedom = 27. The df was calculated based on the total observations (30), the entire study period (2015-16 to 2024-25), and three industries. From the ANOVA table, the within-group sum of squares is 737.6405.

The results above show that the first two rows are

significant, as the mean differences exceed the HSD for both Orient vs Kuantum and Orient vs Pudumjee. However, in the last row, the difference between Kuantum vs Pudumjee is not significant, as HSD exceeds the mean difference. Hence, this indicates that Kuantum & Pudumjee outperformed Orient in terms of capital efficiency and profitability. Hence, the difference in absenteeism between Kuantum & Pudumjee indicates that their ROCE averages are statistically comparable over the study period.

It has been pointed out from the tables above that Kuantum Paper Industry has the highest average recorded for the period 2015-16 to 2024-25, followed by Pudumjee and Orient at 1.778. Furthermore, the p-value (0.031073) is less than 0.05, indicating that the differences in NPR averages across industries are statistically significant. This indicates that the selected industries differ in their ability to convert returns into net profit over the study period. The higher average for Kuantum indicates strong profitability, whereas Orient's lower average reflects weaker profitability.

Tukey's post hoc test for net profit ratio

$$HSD = 3.506 \cdot \sqrt{\frac{29.367}{10}} = 6.01$$

The q value remains the same here because the number of degrees of freedom (df) remains constant or unchanged for both ratios; therefore, q remains the same. The HSD value differs due to variations in the mean within the group sum of squares.

Table 5: Tukey's post hoc test for returns on capital employed (ROCE)

Comparison of industries	Absolute Mean Difference	HSD Critical Value	Significant (Yes/No)
Orient Paper & Industries Ltd vs Kuantum Papers Ltd	3.351-10.386 = 7.035	5.79	Mean Difference > HSD = Yes
Orient Paper Ltd vs Pudumjee Paper Products Ltd	3.351-13.840 = 10.489	5.79	Mean Difference > HSD = Yes
Kuantum Papers Ltd vs Pudumjee Paper Products Ltd	10.386-13.840 = 3.454	5.79	Mean Difference < HSD = No

Source: Author's calculations

Table 6: Summary Statistics for NPR Among Selected Paper Industries

Groups	Count	Average	Variance
Orient	10	1.778	58.376
Kuantum	10	8.476	16.721
Pudumjee	10	6.23	12.975

Source: Author's calculations

Table 7: Analysis of Variance (ANOVA) Results for NPR Among Selected Paper Industries

Source of Variation	SS	df	MS	F	P-value	F crit
Between Groups	232.426	2	116.213	3.959	0.031073	3.354
Within Groups	792.645	27	29.357	---	---	---
Total	1025.072	29	---	---	---	---

Source: Author's calculations

Table 8: Tukey's post hoc test for net profit ratio (NPR)

Comparison	Mean Difference	HSD	Significant (Yes/No)
Orient Paper & Industries Ltd. vs. Kuantum Papers Ltd	1.778-8.476 = 6.698	6.01	Mean Difference > HSD=Yes
Orient Paper & Industries Ltd. vs. Pudumjee Paper Products Ltd	1.778-6.23 = 4.452	6.01	Mean Difference < HSD=No
Kuantum Papers Ltd. vs. Pudumjee Paper Products Ltd	8.476-6.23 = 2.246	6.01	Mean Difference < HSD = No

Source: Author's calculations

The table above shows that the difference between Orient and Kuantum is significant. However, the mean differences are less than the HSD for Orient vs Pudumjee and Kuantum vs Pudumjee, so they are not significant. Thus, this confirms that, among the three industries, Kuantum performs best and shows increasing profits compared to Orient. For Pudumjee, it is consistent with no significant difference from the other two firms. The findings indicate that the overall difference depicted by ANOVA is attributable to the difference in mean NPR (Orient & Kuantum), while Pudumjee does not differ significantly from either of the two industries in the average NPR.

To summarise, Kuantum's superior performance is related to the industry's ability to convert generated sales into profits and make greater returns from capital invested. A higher ROCE represents the optimised use of capital. The improvement after 2020 is associated with the industry's capability to perform productively.

Correlation Matrix of Return on Capital Employed Ratio (ROCE), Total Assets Turnover Ratio (TATR), and Operating Ratio (OR)

$$r = \frac{n \sum XY - (\sum X)(\sum Y)}{\sqrt{[n \sum X^2 - (\sum X)^2][n \sum Y^2 - (\sum Y)^2]}}$$

Pearson's correlation coefficient was used in this paper to estimate the direction of the relationship between ROCE, TATR, and OR.

In the next step, a correlation analysis was conducted to ascertain the direction of the relationship among ROCE, TATR, and OR. The table above shows that TATR has a strong relationship with ROCE, with a correlation coefficient of $r=0.728$, indicating that efficient asset utilisation improves capital management, efficiency, and profitability. On the contrary, the operating ratio shows a negative relationship with ROCE ($r = -0.837$), indicating that higher operating expenses may reduce returns on capital invested. Lastly, the correlation between TATR and OR is also negative ($r = -0.388$), indicating that industries with better skills in asset utilisation achieve lower operating expenses. Additionally, firm-specific factors, including raw material prices, production scale, and production costs, play a significant role in determining operational efficiency. Therefore, it is reasonable to

Table 9:
Pearson Correlation Matrix of ROCE, TATR, and OR

Variables	ROCE	TATR	OR
ROCE	1		
TATR	0.728	1	
OR	-0.837	-0.388	1

Source: Author's calculations

conclude that if assets are utilised effectively with no waste, they will contribute to positive outcomes. In contrast, higher operating expenses will harm industries and turn profits into losses.

Impact of Total Assets Turnover Ratio (TATR) and Operating Ratio (OR) on Returns on Capital Employed (ROCE): Multiple Regression Analysis

$$ROCE = \beta_0 + \beta_1(TATR) + \beta_2(OR) + \varepsilon$$

$$ROCE = 48.280 + 9.280 (TATR) - 0.483 (OR)$$

Table 10: Model Summary of Multiple Regression Analysis for ROCE

Regression Statistics	
Multiple R	0.944
R Square	0.892
Adjusted R Square	0.884
Standard Error	2.292
Observations	30

Source: Author's calculations

In the following phase, a multiple regression analysis was conducted to assess the impact of TATR & OR on ROCE. The results show a high R-squared of 0.892, indicating that 89.2% of the variation in ROCE is explained by TATR & OR. The remaining differences might be related to other firm-associated factors that have not been included in this model. Further, the F statistic is 111.068 with a soaring p-value of 9.36E-14, indicating that the regression model significantly explains the differences in ROCE.

The coefficient of TATR is $\beta = 9.280$ ($p < 0.05$), indicating that an increase in the asset turnover

ratio improves capital efficiency. Whereas OR is negative, $\beta = (-0.483)$, and $p < 0.05$, which states that a rise and elevated increase in operating expenses decreases ROCE.

Therefore, the overall results show that TATR positively determines ROCE, whereas OR negatively influences the profitability. Hence, these results support the ANOVA and correlation findings. Consequently, ROCE was taken as the dependent variable because it is a comprehensive measure of capital management, revealing how effectively an industry generates returns on invested capital.

Hence, these regression results should be represented as relationships rather than definite causal effects, due to the small sample size, including three industries and 30 firm-year observations.

Hausman Specification Test

To determine the appropriate panel regression method, the Hausman specification test was conducted. Here, the null hypothesis states that a random-effects model is more suitable, whereas the alternative hypothesis posits a fixed-effects model. The results indicated a chi-square statistic of 1.3134 with a p-value of 0.5186. Since the p-value is greater than 0.05, the alternative hypothesis is not rejected. Hence, the random-effects model should be considered.

Multicollinearity Test (Variance Inflation Factor)

$$R^2 = 0.150457$$

$$VIF = \frac{1}{1 - R^2}$$

$$Tolerance = 1 - R^2$$

Table 11: ANOVA Results of Multiple Regression Analysis for ROCE

ANOVA					
	<i>df</i>	<i>SS</i>	<i>MS</i>	<i>F</i>	<i>Significance F</i>
Regression	2	1167.235	583.6175	111.0682	9.36498E-14
Residual	27	141.8738	5.254584		
Total	29	1309.109			

Source: Author's calculations

Table 12: Coefficient Estimates of Multiple Regression Analysis for ROCE

Variable	Coefficient	Std. Error	t-Statistic	P-value	Lower 95%	Upper 95%
Intercept	48.280	5.226	9.238	7.55E-10	37.557	59.003
TATR	9.280	1.343	6.910	2.00E-07	6.524	12.035
OR	-0.483	0.051	-9.491	4.30E-10	-0.588	-0.379

Source: Author's calculations

Table 13: Hausman Specification Test Results for Panel Data Model Selection

Chi-square statistic	d.f	Probability
1.3134	2	0.5186

Source: Author's calculations

Table 14: Summary of Diagnostic Test Results for Panel Regression Analysis

Test	Statistic	Result
Hausman Test	1.3134	Random Effects Selected
VIF	1.177	No Multicollinearity

Source: Author's calculations

To examine for multicollinearity, a VIF test was conducted; the VIF was 1.177, below 10. Hence, the estimated variables are reliable, and there is no multicollinearity.

Theoretical Basis for Model Specification

The model's description is based on the resource-based view. ROCE is taken as a dependent variable because it measures the return on capital invested and is therefore a suitable indicator for assessing the results achieved after better utilisation of internal resources. Therefore, the empirical model estimates whether asset utilisation and operational cost efficiency are associated with improved financial performance. The equation is expressed as

$$ROCE = \beta_0 + \beta_1 TATR + \beta_2 OR + \varepsilon$$

Thus, on the basis of theoretical underpinnings, β_1 is anticipated to be positive while β_2 is anticipated to be negative. The model is envisioned to calculate statistical associations among the selected variables and should not be construed as implying causal relationships.

Impact of TATR and Operating Ratio on ROCE using a Random Effects Model

Dependent Variable: Return on Capital Employed (ROCE)

Effects Specification: Cross-section Random Effects

The estimated equation is: $ROCE = 48.2800 + 9.2796(TATR) - 0.4832(OR)$

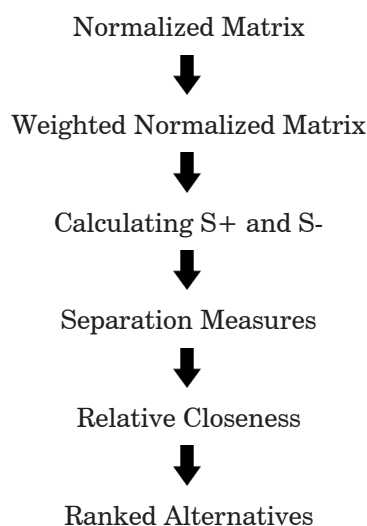
The random-effects model is used here to estimate the impact of TATR & OR on ROCE while controlling for industry differences. The results reveal that TATR has a positive and significant influence on ROCE ($\beta = 9.2796$, $p < 0.01$), explaining that asset utilisation leads to better capital inflow. Comparatively, OR has a significant negative effect on ROCE ($\beta = -0.4832$, $p < 0.01$), thereby confirming the earlier notion that higher expense reduces financial growth.

The R-squared is 0.8916, explaining 89.16% of the variation in ROCE, with TATR and OR as the dominant explanatory variables. The F-statistic value is 111.07, and the p-value of 0.0000 explains that the model is statistically significant.

Hence, the high R-squared and F-statistic in the random-effects model indicate that TATR and OR are important determinants of ROCE, while industry-specific factors strengthen the role of financial performance.

To conclude, multiple regression provides a general explanation of the impact of TATR & OR on ROCE, while the random effects model incorporates the panel structure of the information or data and accounts for unobserved firm-specific heterogeneity. The uniformity of coefficients and significance across the two methods provides greater support for the observed relationships, whereas the small cross-sectional dimension warrants cautious inference.

TOPSIS Analysis



Source: Madanchian and Taherdoost (2023)

Hwang & Yoon (1981) developed TOPSIS, a multi-criteria decision-making model. It uses all the characteristic information and provides a numeric ranking of groups/companies. Also, it accommodates

Table 15: Random Effects Model Results for Return on Capital Employed (ROCE)

Variable	Coefficient	T-statistic	Probability
Constant	48.2800	9.1201	0.0000
TATR	9.2796	6.8220	0.0000
OR	-0.4832	-9.3696	0.0000

Source: Author's calculations

Table 16. Model Summary Statistics of the Random Effects Model

Particulars	Value
R-Squared	0.8916
Adjusted R-Squared	0.8836
F-Statistic	111.07
Prob (F-Statistic)	0.0000
Total Observations	30

Source: Author's calculations

Table 17: Decision Matrix of Selected Paper Industries

Company	GPR	NPR	TATR	OR	ROCE
Orient Paper & Industries Ltd	49.05	1.78	0.38	99.01	3.35
Kuantum Papers Ltd	66.32	8.49	0.56	90.07	10.39
Pudumjee Paper Products Ltd	42.72	6.23	1.11	91.88	13.24

Source: Author's calculations

both the positive and negative aspects of each entity, making it a valuable tool for comparison. Behzadian (2012) & Biswas et al. (2018). Thus, the purpose of the present study is to apply TOPSIS to rank the selected paper industries using the selected financial ratios.

Step 1: Decision Matrix

The decision matrix in step 1 consists of mean values, as they provide more reliable measures than fluctuating values. These are taken for all ratios and for selected paper industries, and represent the average financial performance for 2015-16 to 2024-25, which serves as the basis for ranking.

Step 2: Normalised Decision Matrix

$$R_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^m x_{ij}^2}}$$

Source: Vector normalisation method (Bouhedja et al., 2024)

For example, in the case of the gross profit ratio:

Square the values:

$$49.05^2 = 2405.90$$

$$66.32^2 = 4398.34$$

$$42.72^2 = 1824.99$$

Sum of squares:

$$2405.90 + 4398.34 + 1824.99 = 8629.23$$

Square root:

$$\sqrt{8629.23} = 92.89$$

Divide each value:

$$Orient = \frac{49.05}{92.89} = 0.5280$$

$$Kuantum = \frac{66.32}{92.89} = 0.7139$$

$$Pudumjee = \frac{42.72}{92.89} = 0.4599$$

Normalisation ensures that all values are brought to a common measurement scale so that estimation can be performed and sets the basis for a weighted, normalised matrix. The normalised decision matrix was calculated using the vector-normalised index, where each value is divided by the square root of the sum of the squares of the mean values for that year and the ratio for all selected industries.

Step 3: Weighted Normalized Matrix

$$V_{ij} = w_j \times r_{ij}$$

w_j = weights of ratios

$$Orient = 0.20 \times 0.5280 = 0.1056$$

Table 18: Normalised Decision Matrix of Selected Paper Industries

Company	Norm GPR	Norm NPR	Norm TATR	Norm OR	Norm ROCE
Orient	0.528	0.167	0.292	0.610	0.195
Kuantum	0.714	0.795	0.431	0.555	0.605
Pudumjee	0.460	0.583	0.854	0.566	0.772

Source: Author's calculations

Table 19: Weighted Normalized Matrix of Selected Paper Industries

Company	W-GPR	W-NPR	W-TATR	W-OR	W-ROCE
Orient	0.106	0.033	0.058	0.122	0.039
Kuantum	0.143	0.159	0.086	0.111	0.121
Pudumjee	0.092	0.117	0.171	0.113	0.154

Source: Author's calculations

For all the ratios equal to or of the same weight as 0.20, it was taken, assuming that all the chosen ratios carry equal importance to the overall financial performance of industries.

In the table above, the weighted matrix was calculated by multiplying the normalised values by 0.2 (1/5). Step 3 is important, as assigning weights helps reflect the ranking in the final step. It can be observed that Kuantum showed the maximum GPR & NPR of 0.143 & 0.159, representing increasing profitability. Pudumjee recorded the highest TATR & ROCE of 0.171 & 0.154, representing capital efficiency and asset utilisation. For Orient, the highest OR is 0.122, indicating inefficiency in cash management and rising costs. Therefore, Kuantum and Pudumjee outperform Orient. The latter performs the weakest across all ratios, indicating troubling financial performance.

Step 4: Positive and Negative Ideal Solutions

$$S_i^+ = \sqrt{\sum (v_{ij} - v_j^+)^2}$$

$$S_i^- = \sqrt{\sum (v_{ij} - v_j^-)^2}$$

“Ideal” best (+) represents the most desirable value, and “ideal” worst (-) demonstrates the most undesirable value. Behzadian *et al.* (2012)

For all the ratios except OR, the highest values determine efficiency, but for the latter, the lowest value is considered efficient. The ideal, best, and worst are calculated from step 3 by selecting the maximum and minimum figures. Hence, for OR, the highest value is considered the worst and the lowest is considered the best.

Since OR is a representative cost:

$$S^+ = \min = 0.111$$

$$S^- = \max = 0.122$$

Step 5: TOPSIS Final Ranking of Selected Paper Companies

$$CC_i = \frac{S_i^-}{S_i^+ + S_i^-}$$

Source: ÜÇÜNCÜ *et al.* (2018)

For instance, Kuantum:

$$CC = \frac{0.20786}{0.13251 + 0.20786} = \frac{0.20786}{0.34037} = 0.610688$$

To determine the ranking of the three paper industries, the TOPSIS method is applied. The method is applied because it simultaneously contemplates variables and ranks them accordingly. For the analysis, the following ratios were selected:

Table 20: Positive and Negative Ideal Solutions

Variable	Ideal Best (+)	Ideal Worst (-)
W-GPR	0.143	0.092
W-NPR	0.159	0.033
W-TATR	0.171	0.058
W-OR	0.111	0.122
W-ROCE	0.154	0.039

Source: Author's calculations

Table 21: Overall Ranking of Selected Paper Companies using TOPSIS

Company	S+	S-	Closeness Coefficient	Final Rank
Kuantum Papers Ltd	0.133	0.208	0.611	1
Pudumjee Paper Products Ltd	0.191	0.196	0.507	2
Orient Paper & Industries Ltd	0.165	0.135	0.451	3

Source: Author's calculations

GPR, NPR, TATR, OR, and ROCE.

The outcome of the multi-criteria decision-making method showed that Kuantum Paper Industry (CC=0.611) ranked first, followed by Pudumjee (CC=0.507) and Orient (CC=0.451). The findings confirmed that the performance of the Kuantum paper industry was preeminent, while Orient's was substandard, further strengthening the results from ANOVA, regression, and the fixed-effects model.

Sensitivity Analysis

The TOPSIS method is implemented to provide a comparative representation of financial indicators for the selected paper industries. In the first step, the same weightage (0.20) is assigned to all five indicators because there is no conventional theoretical or empirical basis for assigning greater significance to any one variable. Therefore, this serves as a neutral point to eliminate any subjective arrangement of a single financial ratio.

To assess the sensitivity of the TOPSIS rankings to different weight specifications, a sensitivity analysis is conducted using six weighting schemes. The primary specifications are assigned equal weights of 0.20 to each of five financial ratios. Afterwards, the weight of each indicator is raised to 0.30, while the remaining four receive weights of 0.175, for a total of 1.00. Therefore, Orient ranks third across all selected weights, whereas the ranks of Kuantum & Pudumjee vary under different weighting conditions. When emphasis was placed on equal

weightage for GPR & NPR, Kuantum achieved first rank, whereas when emphasis was placed on TATR, OR, & ROCE, Pudumjee achieved first rank. Hence, the ranking of the two industries is sensitive to the priority given to the ratios or indicators. To sum up, the TOPSIS results are interpreted as a comparative ranking based on relative closeness to the optimal solution, not as evidence of statistically significant differences among the industries.

Trend Analysis

In the next step, trend analysis was conducted for the three selected industries for 2015-16 to 2024-25 for ROCE & NPR. As 2015 was the first selected year, it was taken as a base year, and the value was specified as 100, so the further approaching years were compared against it to estimate the differences over time.

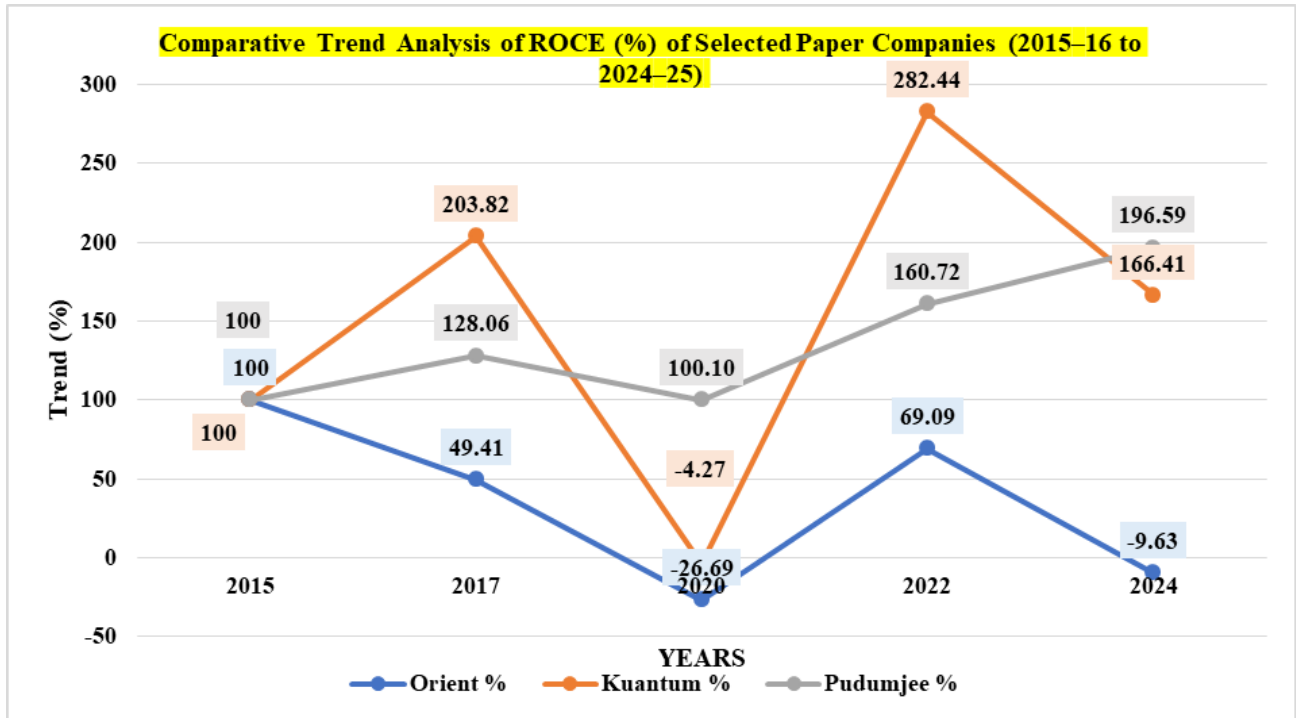
The trend analysis shows fluctuating data for the Orient paper industry, with values turning negative in 2020 and 2021. This period aligns with the pandemic years; however, the present does not make a causal claim about the connection between the pandemic and the observed data, as no COVID-19 model is studied. The recovery was observed in 2022; however, it was only temporary, as the trend decreased again to -9.63 in 2024. Kuantum Paper Industry showed relatively strong performance; despite downturns in 2019 and 2020, the industry recovered in 2022 and reached its highest level of 282.44. Therefore, it represented a strong recovery. Pudumjee Paper Industry displayed uniform growth, indicating efficient capital utilisation. The

Table 22: Sensitivity Analysis of TOPSIS Rankings under Alternative Weighting Schemes

Weighting specification	GPR	NPR	TATR	OR	ROCE	Orient CC	Kuantum CC	Pudumjee CC	Rank 1	Rank 2	Rank 3
Equal weights	0.200	0.200	0.200	0.200	0.200	0.451	0.611	0.507	Kuantum	Pudumjee	Orient
GPR emphasis	0.300	0.175	0.175	0.175	0.175	0.098	0.660	0.652	Kuantum	Pudumjee	Orient
NPR emphasis	0.175	0.300	0.175	0.175	0.175	0.048	0.724	0.709	Kuantum	Pudumjee	Orient
TATR emphasis	0.175	0.175	0.300	0.175	0.175	0.050	0.527	0.784	Pudumjee	Kuantum	Orient
OR emphasis	0.175	0.175	0.175	0.300	0.175	0.061	0.640	0.733	Pudumjee	Kuantum	Orient
ROCE emphasis	0.175	0.175	0.175	0.175	0.300	0.049	0.660	0.785	Pudumjee	Kuantum	Orient

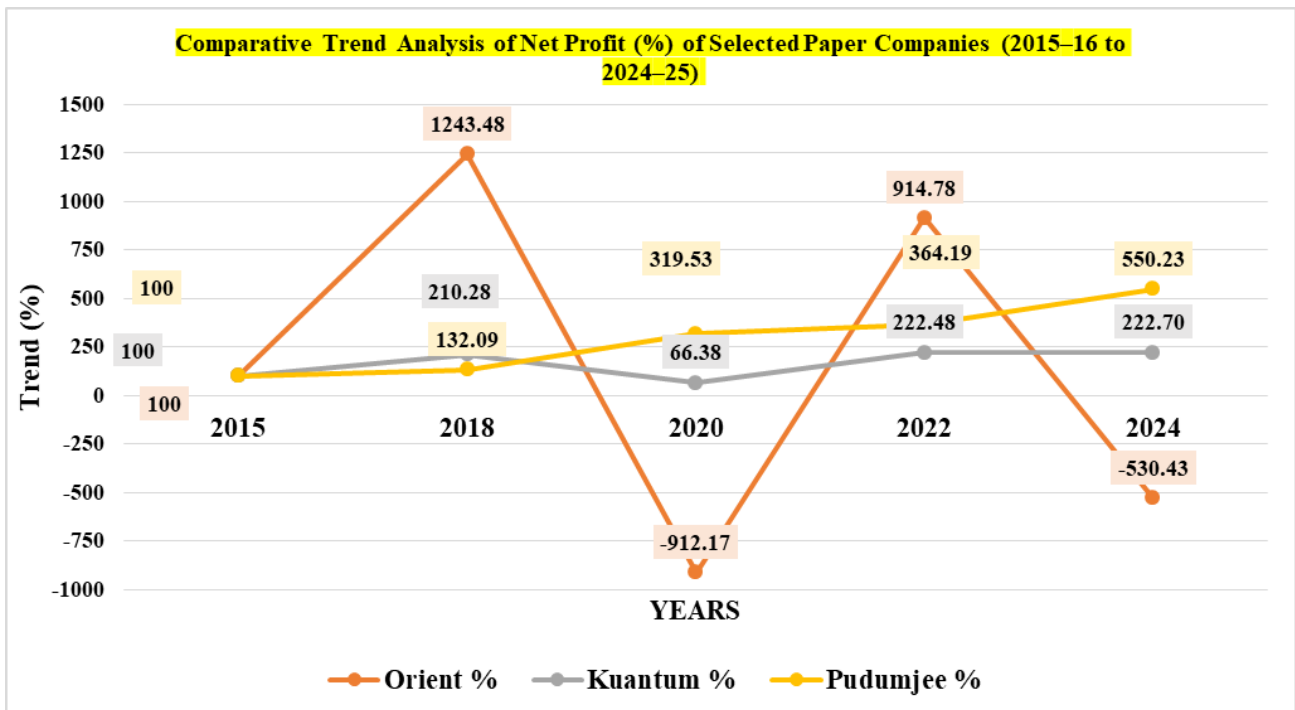
Source: Author's calculations

Figure 1: Comparative Trend Analysis of ROCE of Selected Paper Companies (2015–2024)



Source: Prepared by the author

Figure 2: Comparative Trend Analysis of NPR of Selected Paper Companies (2015–2024)



Source: Prepared by the author

overall data remained consistent, peaking in 2023 at 238.08.

The trend analysis further adds a time dimension to the cross-industry evaluation, showing that the

differences measured above by descriptive and statistical tests are not limited to that but are also reflected in how ROCE evolved over the period examined.

The data for Orient Paper Industry revealed substantial instability. The trend increased sharply to 1243.48 in 2018; however, in 2020 and 2021, the values turned negative, depicting net losses. Although there was a temporary recovery in 2022, it turned negative again in 2024. Hence, this pattern represents inconsistent and volatile movements. Kuantum Paper Industry maintained a positive trend for all the years. Although profits were low in 2020 and 2021, they soon improved. The highest trend can be observed in 2023 at 324.84. Pudumjee Paper Industry demonstrated an improved and uniform pattern. With minor losses in 2018 and 2021, the industry maintained a positive trend throughout. The value was highest in 2023 at 581.40.

Additionally, sustaining profitability over time is more viable than achieving profits in a specific year. Kuantum's robust performance over time reflects its stability and ability to sustain earnings, whereas Pudumjee's trend shows its resilience in fighting back despite setbacks. Therefore, the overall findings show how the profitability positions of three industries evolved, rather than relying solely on their average NPR values.

The 3-year moving average analysis was conducted to smooth short-run volatilities and provide a vivid description of the underlying performance trends of selected paper industries.

Pudumjee exhibited the steadiest improvement. The data reveals that ROCE increased from 12.08 (2015-16 to 2017-18) to 19.81 (2022-23 to 2024-25). Similarly, NPR increased from 3.24 to 10.72. The synchronised improvement in ROCE & NPR represents robustness in generating returns on capital and translating sales into profits. For

Kuantum, the data show an overall positive course trend, with ROCE increasing from 10.66 to 15.90 and NPR from 8.21 to 11.99. In the in-between, the numbers showed a decline, but in subsequent years, they indicate profitability and improvement, indicating recovery in both profit-making and higher capital returns. In contrast, the Orient paper industry is underperforming and shows a prolonged long-term decline. ROCE decreased from 6.47 to 3.05, and NPR from 3.49 to 1.72, with negative values from 2019-20 to 2021-22 indicating considerable deterioration.

Thus, these results complement the earlier trend analysis by establishing that the observed differences persist even after short-run fluctuations are eliminated.

Concluding discussion

The present study displays important differences in the financial performance of the selected Indian paper industries. The results from ANOVA and Tukey's HSD reveal statistically significant differences in ROCE and NPR, indicating that industries had diverse profit-earning and capital-generating patterns. The regression and random-effect result further showed that TATR is positively associated with ROCE, whereas OR is negatively associated with ROCE.

Additionally, the trend and three-year moving average methods describe long-term upward and downward trends. Pudumjee demonstrated a consistent trend; Kuantum is renowned for its recovery and retort, and Orient showed the most volatile performance, including negative profits and capital return figures in multiple years. These results suggest that variations in profit-making,

Table 23: Comparative Moving Average Analysis of ROCE and NPR of Selected Paper Industries (2015–16 to 2024–25)

Period	Orient ROCE	Orient NPR	Kuantum ROCE	Kuantum NPR	Pudumjee ROCE	Pudumjee NPR
2015–16 to 2017–18	6.47	3.49	10.66	8.21	12.08	3.24
2016–17 to 2018–19	5.34	7.87	12.57	9.93	11.83	3.47
2017–18 to 2019–20	5.34	8.30	10.90	9.89	11.63	3.71
2018–19 to 2020–21	2.34	2.36	6.36	7.52	10.70	4.74
2019–20 to 2021–22	-1.16	-4.05	3.97	4.78	11.17	5.86
2020–21 to 2022–23	0.99	-1.63	7.77	5.03	12.23	6.97
2021–22 to 2023–24	2.74	2.11	13.97	9.06	16.82	8.85
2022–23 to 2024–25	3.05	1.72	15.90	11.99	19.81	10.72

Source: Author's calculations

asset optimisation, and higher operating costs may have contributed to the differing scenarios.

Moreover, the implementation of the TOPSIS method yields a ranking in which Kuantum ranks first, Pudumjee second, and Orient needs improvement. Taken together, these findings suggest that strengthening financial performance is linked to cost management and sustaining profitability.

From a managerial viewpoint, the results demonstrate the necessity of regulating and monitoring production costs, asset productivity, and maximization of capital earnings. These, in turn, link to profit gains and, hence, to improved financial statements. These findings may also aid investors, policymakers, researchers, and other interested parties in understanding variations in financial performance across India's three paper industries.

The present paper provides a longitudinal perspective spanning pre- and post-COVID years. However, the results should not be used as evidence of a causal effect of COVID-19, as the analysis does not estimate a COVID-19 model. To conclude, the study contributes to the existing literature by providing a comprehensive assessment of three paper industries that are comparatively under-researched in this sector. The sample taken is small, that is, of three industries and 30 firm-year observations, so the results should not be taken as a generalisable evaluation for the entire paper sector, but rather should be taken as specific comparative evidence on the three industries.

Limitations and Future Scope of the Study

The major limitations of the present study are, firstly, that it is limited to three paper industries and thus may not represent the entire Indian paper industry. Secondly, the data span covers the period from 2015-16 to 2024-25. Third, the study is heavily dependent on secondary data extracted from the PROWESS database. Fourth, the main objective of the paper is to calculate profitability; hence, only the specific ratios were taken to analyse the results.

Future directions for the study may include additional paper industries to enable widespread generalisation. Secondly, there can be a comparative study including various other sectors, such as iron & steel, textiles, and so on. Third, the aspects of corporate governance and environmental sustainability may be considered. Lastly, more

extensive econometric methods, such as dynamic panel models, can be applied.

Declaration of Conflicting Interests

The author declared no potential conflicts of interest with respect to the research, authorship and/or publication of this article.

Acknowledgments

The authors would like to express their sincere gratitude to their institution and to all who provided support and encouragement throughout this research. The authors also acknowledge the use of the CMIE Prowess database for providing the financial data used in the study.

Funding

The author received no financial support for the research, authorship and/or publication of this article.

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Appendix A:

Below is the data taken from Prowess – CMIE for the following ratios:

Table 1: Gross Profit Ratio

Years	Orient	Kuantum	Pudumjee
2015-16	41.67	63.66	38.36
2016-17	-93.68	65.88	41.21
2017-18	71.80	68.50	42.29
2018-19	71.82	66.40	37.95
2019-20	68.34	64.87	43.42
2020-21	68.84	63.88	47.1
2021-22	69.70	63.01	44.7
2022-23	68.88	69.00	40.0
2023-24	65.92	70.47	46.25
2024-25	57.19	67.52	45.87

Source: Prepared by the author using data from PROWESS

Table 1.1: Statistics Summary of Gross Profit Ratio

	Orient	Kuantum	Pudumjee
Mean (Average)	49.05	66.32	42.72
Median	68.59	66.14	42.86
Standard Deviation	50.99	2.52	3.30
Minimum	-93.68	63.01	37.95
Maximum	71.82	70.48	47.13
Range	165.51	7.47	9.18
Coefficient of Variation (%)	103.95	3.79	7.72
Skewness	-2.98	0.27	-0.18
Kurtosis	9.10	-1.15	-1.41

Source: Author's calculations

Table 2: Net Profit Ratio

Years	Orient	Kuantum	Pudumjee
2015-16	1.15	4.67	2.15
2016-17	1.98	9.76	3.78
2017-18	7.33	10.20	3.78
2018-19	14.3	9.82	2.84
2019-20	3.28	9.64	4.50
2020-21	-10.49	3.1	6.87
2021-22	-4.93	1.61	6.22
2022-23	10.52	10.39	7.83
2023-24	0.74	15.17	12.50

2024-25	-6.10	10.40	11.83
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Source: Prepared by the author using data from PROWESS

Table 2.1: Summary Statistics of Net Profit Ratio

	Orient	Kuantum	Pudumjee
Mean (Average)	1.78	8.49	6.23
Median	1.57	10.01	5.36
Standard Deviation	7.80	4.04	3.45
Minimum	-10.50	1.62	2.16
Maximum	14.32	15.18	12.50
Range	24.81	13.56	10.35
Coefficient of Variation (%)	438.20	47.60	55.40
Skewness	-0.10	-0.20	0.67
Kurtosis	-0.76	0.90	-0.64

Source: Author's calculations

Table 3: Total Assets Turnover Ratio

Years	Orient	Kuantum	Pudumjee
2015-16	0.78	0.59	1.09
2016-17	0.30	0.6	1.34
2017-18	0.37	0.64	1.14
2018-19	0.39	0.62	1.22
2019-20	0.36	0.48	1.17
2020-21	0.22	0.25	0.79
2021-22	0.26	0.49	0.93
2022-23	0.43	0.77	1.21
2023-24	0.34	0.64	1.09
2024-25	0.37	0.52	1.06

Source: Prepared by the author using data from PROWESS

Table 3.1: Summary Statistics of Total Assets Turnover Ratio

	Orient	Kuantum	Pudumjee
Mean (Average)	0.38	0.56	1.11
Median	0.36	0.59	1.12
Standard Deviation	0.15	0.14	0.15
Minimum	0.23	0.25	0.79
Maximum	0.78	0.77	1.34
Range	0.56	0.52	0.54
Coefficient of Variation (%)	39.75	24.67	13.89
Skewness	2.26	-1.06	-0.74
Kurtosis	6.30	2.55	0.88

Source: Author's calculations

Table 4: Operating Ratio

Years	Orient	Kuantum	Pudumjee
2015-16	96.97	93.94	98.94
2016-17	102.60	87.39	94.16
2017-18	89.75	85.52	94.71
2018-19	86.43	87.14	96.21
2019-20	98.49	92.42	94.07

2020-21	116.32	108.24	88.28
2021-22	109.06	99.54	90.23
2022-23	87.43	79.93	90.62
2023-24	101.37	80.0	84.94
2024-25	111.68	86.51	86.67

Source: Prepared by the author using data from PROWESS

Table 4.1: Summary Statistics of Operating Ratio

	Orient	Kuantum	Pudumjee
Mean (Average)	99.01	90.07	91.88
Median	100.18	87.26	92.20
Standard Deviation	10.74	8.82	4.60
Minimum	86.43	79.93	84.94
Maximum	116.32	108.24	98.94
Range	29.89	28.31	14
Coefficient of Variation (%)	10.85	9.79	5.01
Skewness	0.40	0.64	0.19
Kurtosis	-1.45	-0.51	-0.76

Source: Author's calculations

Table 5: Return on Capital Employed Ratio

Years	Orient	Kuantum	Pudumjee
2015-16	11.84	6.55	9.98
2016-17	1.72	12.07	13.47
2017-18	5.85	13.35	12.78
2018-19	8.45	12.28	9.24
2019-20	1.73	7.08	12.86
2020-21	-3.16	-0.28	9.99
2021-22	-2.06	5.1	10.66
2022-23	8.18	18.50	16.04
2023-24	2.1	18.31	23.76
2024-25	-1.14	10.90	19.62

Source: Prepared by the author using data from PROWESS

Table 5.1: Summary Statistics of Capital Employed Ratio

Statistic	Orient	Kuantum	Pudumjee
Mean (Average)	3.35	10.39	13.24
Median	1.92	11.49	12.82
Standard Deviation	4.90	6.27	4.68
Minimum	-3.16	-0.28	9.24
Maximum	11.84	18.50	23.76
Range	15.00	18.78	14.52
Coefficient of Variation (%)	146.27	60.32	35.35
Skewness	0.44	-0.29	1.35
Kurtosis	-1.09	-0.97	1.37

Source: Author's calculations

Risk–Return Dynamics and Risk-Adjusted Performance of Selected Indian IT Stocks: A CAPM-Based Analysis

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Citation: Ittoop, J., & Lawrence, A. (2026). Risk–Return Dynamics and Risk-Adjusted Performance of Selected Indian IT Stocks: A CAPM-Based Analysis. *Indian Journal of Accounting*, 58(1), 107-117

ABSTRACT

The Information Technology (IT) sector occupies a significant position in the Indian economy and capital market, with leading IT companies attracting substantial investor interest. This study comparatively evaluates the risk–return characteristics and risk-adjusted performance of five selected Indian IT stocks – Tata Consultancy Services (TCS), Infosys, HCL Technologies, Wipro, and Tech Mahindra – during the period from January 2021 to December 2025. The study is based entirely on secondary data, comprising monthly stock prices of the selected companies and the NIFTY 50 index as a proxy for market performance. Descriptive and analytical techniques, including mean return, standard deviation, Beta, Sharpe Ratio, Treynor Ratio, Jensen’s Alpha, and the Capital Asset Pricing Model (CAPM), were employed to assess the investment performance of the selected stocks. One-way ANOVA was also applied to examine whether significant differences existed in the mean returns of the selected companies.

The findings reveal considerable variation in the risk–return profiles of the selected IT stocks. HCL Technologies recorded the highest mean return, while TCS exhibited the lowest volatility. Tech Mahindra recorded the highest standard deviation and Beta, indicating comparatively greater total and systematic risk. HCL Technologies demonstrated the strongest risk-adjusted performance, recording the highest Sharpe and Treynor ratios and a positive Jensen’s Alpha, followed by Tech Mahindra. In contrast, TCS recorded negative values for all three risk-adjusted performance measures. The CAPM analysis further revealed that HCL Technologies and Tech Mahindra generated actual returns above their respective CAPM-expected returns, whereas TCS, Infosys, and Wipro generated returns below their expected levels. However, the ANOVA results indicated that the differences in mean returns among the selected IT stocks were not statistically significant. The study concludes that evaluating IT stocks solely on the basis of absolute returns may not provide a comprehensive assessment of investment performance. A combined consideration of total risk, systematic risk, risk-adjusted returns, and CAPM-based expected returns provides a more meaningful basis for investment evaluation.

Keywords

Information Technology Stocks, Risk–Return Analysis, Sharpe Ratio, Treynor Ratio, Jensen’s Alpha, CAPM, Beta, Indian Stock Market.

Introduction

The Information Technology (IT) sector has developed as one of the most influential and rapidly growing sectors of the Indian economy. In recent decades, India has developed into a global technology and outsourcing hub, with major IT companies playing a significant role in economic development, employment generation, export earnings, and technological advancement. Leading

companies such as Tata Consultancy Services (TCS), HCL Technologies, Wipro, Infosys and Tech Mahindra have established strong positions not only in the domestic market but also in the international business environment. Due to their consistent growth and strong market reputation, the stocks of these companies attract significant attention from both retail and institutional investors.

Although these companies belong to the same

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industry and operate under similar economic and market conditions, their stock performance varies considerably in terms of returns, risk levels, volatility, and responsiveness to market fluctuations. Investors generally focus on returns while making investment decisions; however, analysing returns alone may not provide a complete understanding of the actual performance of a stock. Greater returns are often related with higher levels of risk, making it essential to evaluate investments on a risk-adjusted basis. Therefore, a detailed analysis of both risk and return becomes necessary to identify companies that provide superior investment performance with efficient risk management.

In the modern investment environment, risk-adjusted performance analysis has become an important tool for evaluating the efficiency of stocks and portfolios. Measures including the Sharpe Ratio, Treynor Ratio, and Jensen's Alpha help investors assess how effectively a stock generates returns relative to the level of risk incurred. These measures provide a more scientific and reliable basis for comparison than traditional return analysis. In addition, the CAPM plays a vital role in examining the relationship between stock returns and overall market movements by measuring systematic risk through beta.

The present study focuses on a comparative performance analysis of selected IT stocks in India, namely Tata Consultancy Services (TCS), Infosys, Wipro, HCL Technologies and Tech Mahindra. This study aims to evaluate and compare the risk-return characteristics and risk-adjusted performance of these companies using various financial and statistical tools. By applying measures such as Standard Deviation, Beta, Sharpe Ratio, Treynor Ratio, Jensen's Alpha, and CAPM, the research seeks to determine whether the performance of these IT companies is driven by operational efficiency and superior management practices or merely influenced by overall market trends.

The Information Technology sector holds a significant position in the Indian economy and the stock market, with major companies such as Tata Consultancy Services (TCS), Infosys, Wipro, HCL Technologies and Tech Mahindra attracting considerable attention from investors. Although these companies operate within the same industry, their stock performance differs in terms of returns, risk levels, and sensitivity to overall market movements. Investors often evaluate stocks mainly

based on returns; however, such an approach may not fully reflect the level of risk involved in the investment. As a result, identifying the company that provides better risk-adjusted performance becomes challenging. Therefore, it is necessary to analyse the performance of selected IT companies by considering both risk and return. This study attempts to evaluate and compare the performance of selected IT sector stocks using risk-adjusted measures such as the Sharpe Ratio, Treynor Ratio, and Jensen's Alpha, along with the CAPM, in order to understand whether their performance is driven by superior efficiency or general market movements.

Review of Literature

The first theme in the existing literature concerns risk-return analysis and comparative stock performance. Several studies have established the importance of evaluating both risk and return instead of relying solely on absolute returns. Patjoshi and Nandini (2020) compared the risk-return performance of the BSE and selected steel companies and found that the Sensex generated better returns with comparatively lower risk. Subramanyam and Kalyan (2018) examined selected infrastructure securities using average return, risk measures, and coefficient of variation and reported considerable differences in risk-return performance. Similarly, Patjoshi (2016) and Naveen and Mallikarjunappa (2016) found variations in returns and risk among selected banking stocks, reinforcing the importance of considering investors' risk-bearing capacity while evaluating securities. Narayanaswamy et al. (2021) also demonstrated that selected automobile companies differed considerably in their return and risk characteristics and emphasized the need to consider both systematic and unsystematic risk in investment decisions.

A second theme relates to volatility, market sensitivity, and systematic risk. Suneetha and Aithal (2024) compared IT and FMCG stocks and found that IT stocks exhibited greater volatility and sensitivity to market fluctuations, suggesting higher risk as well as greater return potential. Yaragatti, Yaragatti, and Sumant (2025), in their study of automobile companies, employed Mean, Standard Deviation, Beta, Alpha, and ANOVA and found substantial differences in volatility and market sensitivity among the selected firms. At the broader market level, Ali and Dembo (2025) analysed Indian stock-market volatility using GARCH-family models and identified volatility clustering,

asymmetric volatility, and long-memory behaviour. Their findings highlighted the significance of volatility analysis for risk management and investment decisions. These studies jointly indicate that market sensitivity and volatility are important determinants of stock performance and should be incorporated into comparative investment analysis.

The third theme focuses on CAPM and risk-adjusted performance evaluation. CAPM has been largely applied to assess the relationship between expected return and systematic risk. Elbannan (2015) reviewed the theoretical foundations, assumptions, limitations, and applications of CAPM and highlighted the importance of Beta in estimating expected returns. Poornima and Swathiga (2017) applied CAPM to selected healthcare and pharmaceutical stocks using Average Return, Standard Deviation, Beta, and expected return and found considerable differences in risk-return profiles. Bheemeswara Reddy and Harish (2024) similarly applied CAPM to selected BSE stocks to identify securities whose actual returns exceeded their expected returns. In addition, Mishra, Mishra, and Patra (2025) evaluated Indian index funds using the Sharpe Ratio, Treynor Measure, and Jensen's Alpha and found that most of the funds generated superior risk-adjusted returns. Yang et al. (2025) further demonstrated the growing importance of risk-adjusted performance by developing a model for predicting Sharpe ratios.

The fourth theme is concerned with financial and market performance of Indian IT companies. Recent studies have particularly examined the financial performance of major Indian IT firms. Bhavini and Joshi (2025) analysed selected IT companies using ratio analysis and ANOVA and found that TCS performed strongly in terms of net profit ratio, return on assets, and earnings per share, whereas Wipro recorded comparatively weaker performance. Anitha, Prasath, and Rupadharshine (2025) conducted a comparative study of TCS, Infosys, Wipro, HCL Technologies and Tech Mahindra for 2019–2024 using revenue growth, profitability, and ROE, while also considering economic, industry, and company-level factors. Podile Raju and Durga (2025) examined the same major IT companies for 2019–2023 using ratio and trend analysis and reported generally stable financial performance and growth. Earlier, Vasantha, Dhanraj, and Varadharajan (2012) examined stock-price movements of major IT companies using

technical indicators such as RSI, Bollinger Bands, MACD, and SMA. These studies establish the significance of Indian IT companies as an area of stock-performance research but primarily focus on financial, operational or technical indicators.

The fifth theme concerns the broader determinants of stock performance and the research gap. Existing studies show that stock performance can be influenced by corporate fundamentals, investor behaviour, technical indicators, macroeconomic conditions, and interactions among different markets. Bagchi (2023) found that EVA, EPS, and P/E ratio significantly influenced stock prices, while Jetty Ravi Sankar and N. Udaya Bhaskar (2023) highlighted the influence of behavioural biases on investment decisions. Agrawal et al. (2025) demonstrated that combining sentiment and technical indicators can improve stock-price prediction. The literature also reveals that, although studies have examined Indian IT companies and risk-return performance separately, limited research has comprehensively compared leading Indian IT stocks using a combination of Standard Deviation, Beta, Sharpe Ratio, Treynor Ratio, Jensen's Alpha, and CAPM. Furthermore, there is limited recent evidence covering January 2021 to December 2025, a period characterized by post-pandemic recovery, rapid digital transformation, changing global economic conditions, and increasing adoption of emerging technologies. Consequently, the present study seeks to address this gap by providing an integrated comparative assessment of the risk-return and risk-adjusted performance of TCS, Infosys, HCL Technologies, Wipro, and Tech Mahindra.

Objectives of the Study

- Analyse and compare the risk and return characteristics of selected IT stocks in India.
- Evaluate the risk-adjusted performance of selected IT Stocks using the Sharpe Ratio, Treynor Ratio, and Jensen's Alpha.
- Examine the relationship between the stock returns of selected IT companies and market movements using the Capital Asset Pricing Model.

Hypothesis

- H₀₁: There is no significant difference in the risk and return characteristics of selected IT stocks in India.
- H₀₂: There is no significant difference in the risk-adjusted performance of selected IT company stocks.

- H₀₃: There is no significant relationship between stock returns of selected IT companies and market returns.

Research Methodology

The current study is based entirely on secondary data. The study adopts an analytical and descriptive research design. It is descriptive in nature as it explains the risk–return characteristics of the selected IT stocks, and analytical as it applies financial models such as the Capital Asset Pricing Model (CAPM) and risk-adjusted performance measures to derive meaningful conclusions from historical data.

The key data used for the study includes monthly closing stock prices of the five IT companies listed in NSE and NIFTY 50 index data, which is used as a proxy for market performance. Five Information Technology (IT) companies selected for the study were Tata Consultancy Services (TCS), Infosys, HCL Technologies, Wipro and Tech Mahindra.

The study adopts a random sampling technique for the selection of companies from the Indian Information Technology (IT) sector. The selected companies were chosen randomly from the Nifty IT.

The secondary data has been obtained from official websites such as the National Stock Exchange (NSE) and Bombay Stock Exchange (BSE), along with financial database platforms like Yahoo Finance and Investing.com.

Results And Discussion

Risk–Return Characteristics of Selected IT Stocks

The risk–return analysis reveals considerable variation in the performance characteristics of the selected Indian IT companies. The mean return ranged from 0.002547 for Tata Consultancy

Services (TCS) to 0.012574 for HCL Technologies, while the standard deviation ranged from 0.061769 to 0.077167. TCS recorded the lowest mean return and the lowest standard deviation, indicating a relatively stable but low-return investment profile. In contrast, HCL Technologies and Tech Mahindra recorded the highest mean returns of 0.012574 and 0.012461, respectively, but were also associated with relatively higher volatility.

HCL Technologies exhibited the strongest return-generating capability among the selected companies, although its higher standard deviation of 0.072501 indicates greater fluctuations in returns. Tech Mahindra recorded a similar mean return but the highest standard deviation (0.077167), suggesting the greatest volatility. Infosys generated a moderate mean return of 0.00682 with a standard deviation of 0.067179, reflecting a relatively balanced risk–return profile. Wipro also recorded a moderate mean return of 0.006478 but exhibited comparatively higher volatility (0.07192), together with the lowest minimum return of –0.199564, indicating relatively greater downside risk. See Table 6.1 and Figure 6.1 for details.

The range of returns further highlights differences in the risk profiles of the companies. Wipro recorded the lowest minimum return (–0.199564), indicating the highest observed downside movement, whereas Tech Mahindra recorded the highest maximum return (0.196856), reflecting stronger upside potential. TCS, despite having the lowest standard deviation, recorded a relatively broad range between its minimum and maximum returns. Overall, the findings indicate a broad risk–return trade-off in which HCL Technologies and Tech Mahindra combine relatively higher returns with higher risk, whereas TCS represents a comparatively conservative investment profile. See Figure 6.2.

Table 6.1
Risk and Return Analysis of Selected IT Companies

Company	Mean Return	Risk (Std. Deviation)	Minimum Return	Maximum Return
TCS	0.002547	0.061769	-0.152989	0.195424
Infosys	0.00682	0.067179	- 0.1779333	0.192437
HCL	0.012574	0.072501	-0.166553	0.158771
Wipro	0.006478	0.07192	-0.199564	0.189839
Tech Mahindra	0.012461	0.077167	0.1739983	0.196856

Source: Researchers' Computation

Figure 6.1
Risk & Return Analysis of selected IT Stocks

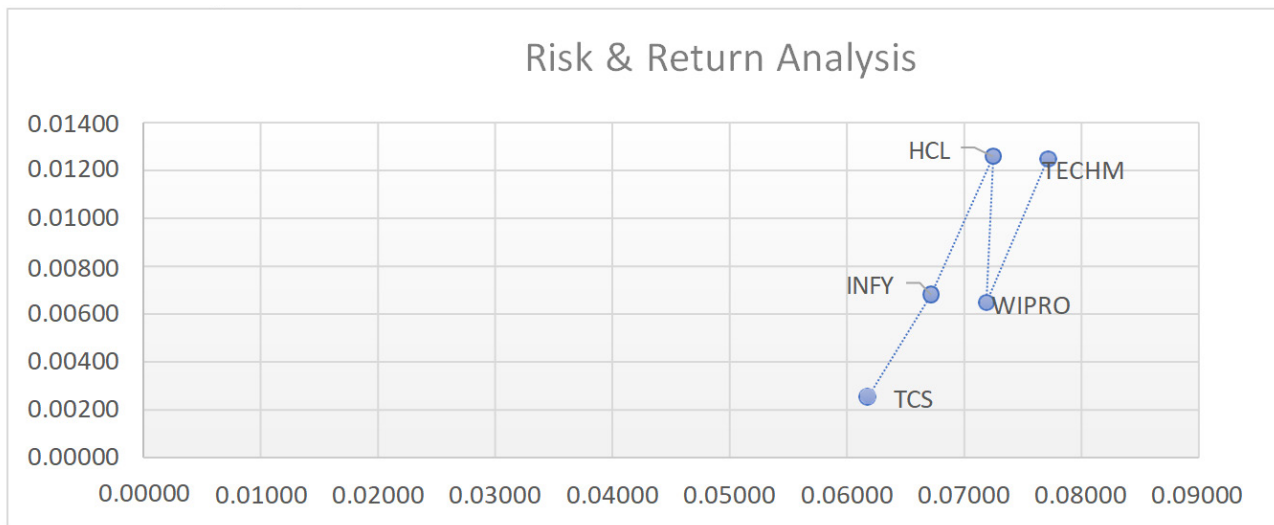
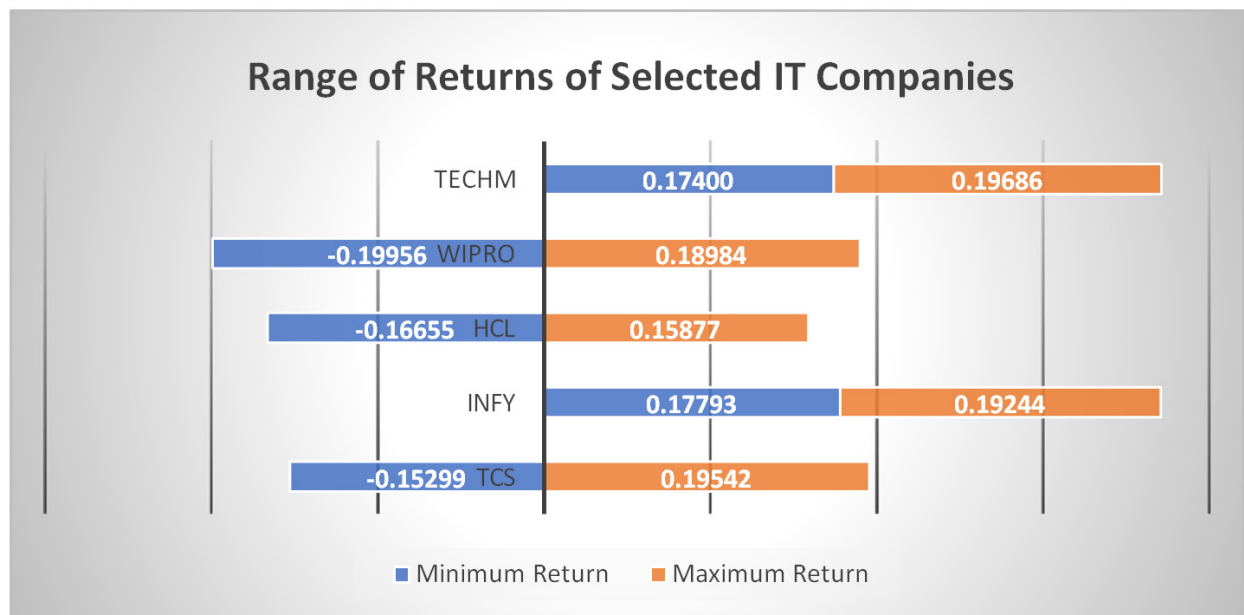


Figure 6.2
Range of Returns of selected IT Companies



To determine whether the differences in mean returns were statistically significant, a one-way ANOVA was conducted. The analysis produced an F-value of 0.22 and a p-value of 0.9265. Since the p-value exceeds the 5 per cent significance level, the observed differences in mean returns are not statistically significant. Thus, although the selected IT companies exhibit observable differences in their individual risk and return characteristics, the evidence does not establish a statistically significant difference in their mean returns during the study period. Details are shown in Table 6.2

Risk-Adjusted Performance

The risk-adjusted performance analysis based on the Sharpe ratio, Treynor ratio and Jensen's alpha demonstrates differences in the efficiency with which the selected IT companies generated returns relative to the risks undertaken. HCL Technologies emerged as the strongest performer, recording the highest Sharpe ratio (0.107), the highest Treynor ratio (0.0083), and a positive Jensen's alpha of 0.0013. These results indicate comparatively superior risk-adjusted performance and suggest that HCL Technologies generated relatively better returns for the level of risk assumed.

Table 6.2
One-Way ANOVA for Mean Returns of Selected IT Companies

Source of Variation	Sum of Squares (SS)	df	Mean Square (MS)	F-value	p-value
Between Groups	0.004373	4	0.001093	0.22	0.9265
Within Groups	1.433297	290	0.004942		
Total	1.43767	294			

Source: Researchers' Computation

Table 6.3
Risk-Adjusted Performance Measures of Selected IT Companies

Company	Beta (β)	Sharpe	Treynor	Jensen Alpha
TCS	0.977	-0.036	-0.0023	-0.009
Infosys	0.806	0.03	0.0025	-0.0036
HCL	0.934	0.107	0.0083	0.0013
Wipro	0.882	0.023	0.0019	-0.0044
Tech Mahindra	1.013	0.099	0.0076	0.0007

Source: Researchers' Computation

Tech Mahindra also demonstrated strong risk-adjusted performance. It recorded a Sharpe ratio of 0.099 and a Treynor ratio of 0.0076, both of which were among the highest values in the sample. Its positive Jensen's alpha of 0.0007 further indicates marginal outperformance relative to the return expected under the CAPM framework. Thus, HCL Technologies and Tech Mahindra demonstrate comparatively stronger risk-adjusted performance among the selected IT companies.

In contrast, TCS recorded a negative Sharpe ratio (-0.036), a negative Treynor ratio (-0.0023), and a negative Jensen's alpha (-0.009). These values indicate comparatively weak risk-adjusted performance and suggest that the returns generated by TCS were inadequate relative to both total and systematic risk. Infosys and Wipro recorded positive but relatively low Sharpe and Treynor ratios, indicating moderate risk-adjusted performance. However, both companies recorded negative Jensen's alpha values, suggesting underperformance relative to CAPM-based expected returns. See Table 6.3.

Taken together, the risk-adjusted measures suggest that the selected IT companies did not perform uniformly. HCL Technologies demonstrated the most favourable overall risk-adjusted performance, followed by Tech Mahindra, whereas TCS exhibited the weakest performance on the selected measures. These results point to meaningful differences in investment efficiency across the selected IT stocks.

Market Sensitivity and CAPM Performance

The CAPM analysis provides further evidence of differences in the market sensitivity and expected performance of the selected IT stocks. Beta values ranged from 0.806 for Infosys to 1.013 for Tech Mahindra. Infosys recorded the lowest beta, indicating comparatively lower sensitivity to market movements, while Tech Mahindra recorded the highest beta, indicating slightly greater sensitivity than the market. TCS recorded a beta of 0.977, HCL Technologies 0.934, and Wipro 0.882, suggesting that these stocks generally exhibited systematic risk below or close to the market level.

A comparison of actual and CAPM-expected returns shows that HCL Technologies and Tech Mahindra generated returns above their respective CAPM expectations. HCL Technologies recorded an actual return of 0.0126 compared with an expected return of 0.0113, while Tech Mahindra recorded an actual return of 0.0125 against an expected return of 0.0118. This indicates marginal outperformance relative to the returns required for their respective levels of systematic risk.

Conversely, TCS, Infosys and Wipro recorded actual returns below their respective CAPM-expected returns. The highest difference was observed for TCS, where the actual return of 0.0025 was substantially below the expected return of 0.0115. Infosys recorded an actual return of 0.0068 against an expected return of 0.0104, while Wipro recorded 0.0065 against an expected return of 0.0109. These

Table 6.4
CAPM Analysis of Selected IT Companies

Company	Beta (β)	Actual Return	CAPM Return
TCS	0.977	0.0025	0.0115
Infosys	0.806	0.0068	0.0104
HCL	0.934	0.0126	0.0113
Wipro	0.882	0.0065	0.0109
Tech Mahindra	1.013	0.0125	0.0118

Source: Researchers' Computation

results demonstrate that these companies did not generate returns commensurate with their systematic risk during the study period.

The observed differences in actual and expected returns may be associated with broader market and company-specific conditions during the study period, including post-pandemic economic recovery, geopolitical uncertainty, market volatility and firm-specific performance. Therefore, the CAPM results indicate that market risk was an important component of the return behaviour of the selected IT stocks, while individual companies differed in their ability to generate returns relative to their systematic risk.

Overall Discussion

The findings provide a differentiated picture of the investment performance of the selected Indian IT companies. HCL Technologies consistently emerges as the strongest performer across the principal measures. It recorded the highest mean return, a relatively high but not the highest level of volatility, the highest Sharpe and Treynor ratios, positive Jensen's alpha, and an actual return exceeding its CAPM-expected return. These results collectively suggest comparatively efficient risk-return performance.

Tech Mahindra also demonstrated an aggressive growth-oriented profile. Its mean return was almost identical to that of HCL Technologies, while its standard deviation and beta were the highest among the selected companies. Its positive Sharpe ratio, Treynor ratio and Jensen's alpha, together with actual returns exceeding CAPM expectations, indicate strong return-generating potential accompanied by relatively high market and total risk.

Infosys represents a comparatively balanced investment profile, with moderate return, moderate volatility and the lowest beta among the selected

companies. However, its actual return remained below its CAPM-expected return, and its negative Jensen's alpha indicates that the stock did not fully compensate investors relative to its expected systematic risk.

Wipro exhibited moderate returns but comparatively greater downside risk. Its low positive Sharpe and Treynor ratios and negative Jensen's alpha indicate relatively limited risk-adjusted efficiency. The particularly low minimum return further highlights its vulnerability to adverse movements.

TCS presents the most conservative risk profile, with the lowest standard deviation and beta close to one, but it also generated the lowest mean return. Its negative Sharpe ratio, Treynor ratio and Jensen's alpha, together with the substantial difference between actual and CAPM-expected returns, indicate weaker risk-adjusted performance despite comparatively lower volatility.

Overall, the outcome of the study suggest that higher returns among the selected IT stocks were generally accompanied by greater volatility, although the differences in mean returns were not statistically significant. The combined risk-return, risk-adjusted and CAPM analyses identify HCL Technologies as the most favourable performer, Tech Mahindra as a higher-risk growth-oriented stock, Infosys as a relatively balanced performer, Wipro as comparatively less efficient, and TCS as a stable but lower-return investment. The findings therefore demonstrate that evaluation based solely on average returns may not adequately capture the investment attractiveness of IT stocks; consideration of total risk, systematic risk and risk-adjusted performance provides a more comprehensive basis for assessing their investment characteristics.

Conclusion

The present study examined the comparative

performance of selected Information Technology companies in India during 2021–2025 using various statistical and financial performance measures. The findings revealed differences in return generation, volatility, risk-adjusted performance, and market sensitivity, although the One-Way ANOVA results indicated that the differences in mean returns were not statistically significant. HCL Technologies and Tech Mahindra emerged as comparatively superior performers, with higher returns and stronger risk-adjusted performance, while TCS exhibited lower volatility and lower return potential. Infosys and Wipro demonstrated moderate risk–return characteristics during the study period.

The study highlights the importance of evaluating investment performance on a risk-adjusted basis rather than relying solely on absolute returns. The Sharpe Ratio, Treynor Ratio, Jensen's Alpha, Beta, and CAPM provided broader insights into the relationship between returns and the risks undertaken. Overall, effective investment decisions in the Indian IT sector require a comprehensive assessment of both risk and return. The findings may assist investors, financial analysts, researchers, and portfolio managers in evaluating the relative performance of IT companies and making informed investment decisions.

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APPENDIX

Month	TCS	INFY	HCL	WIPRO	TECHM	NIFTY 50
Jan-21	3,036	1,232	904	209	910	13,635
Feb-21	2,824	1,246	900	205	870	14,529
Mar-21	3,100	1,360	972	207	939	14,691
Apr-21	2,962	1,347	899	246	909	14,631
May-21	3,082	1,386	945	270	967	15,583
Jun-21	3,264	1,572	984	273	1,037	15,722
Jul-21	3,090	1,601	1,025	294	1,160	15,763
Aug-21	3,694	1,697	1,182	320	1,389	17,132
Sep-21	3,684	1,666	1,280	317	1,324	17,618
Oct-21	3,315	1,658	1,144	323	1,418	17,672
Nov-21	3,443	1,703	1,139	319	1,493	16,983
Dec-21	3,647	1,877	1,319	358	1,735	17,354
Jan-22	3,645	1,726	1,099	286	1,433	17,340
Feb-22	3,468	1,706	1,127	278	1,366	16,794
Mar-22	3,649	1,896	1,164	296	1,453	17,465
Apr-22	3,460	1,559	1,079	254	1,220	17,103
May-22	3,282	1,495	1,041	239	1,143	16,585
Jun-22	3,187	1,454	973	208	969	15,780
Jul-22	3,221	1,541	948	212	1,031	17,158
Aug-22	3,133	1,485	939	207	1,058	17,759
Sep-22	2,931	1,406	932	197	991	17,094
Oct-22	3,115	1,529	1,041	193	1,045	18,012
Nov-22	3,308	1,626	1,121	203	1,077	18,758
Dec-22	3,177	1,500	1,039	196	1,016	18,105
Jan-23	3,343	1,525	1,122	199	1,015	17,662
Feb-23	3,298	1,479	1,078	194	1,100	17,304
Mar-23	3,191	1,420	1,085	183	1,102	17,360
Apr-23	3,204	1,246	1,064	193	1,024	18,065
May-23	3,274	1,311	1,145	202	1,116	18,534
Jun-23	3,287	1,328	1,188	195	1,131	19,189
Jul-23	3,406	1,348	1,117	203	1,116	19,754
Aug-23	3,341	1,427	1,172	204	1,202	19,254
Sep-23	3,512	1,427	1,235	203	1,223	19,638
Oct-23	3,353	1,361	1,276	191	1,133	19,080
Nov-23	3,472	1,447	1,341	207	1,221	20,133
Dec-23	3,776	1,534	1,466	236	1,273	21,731
Jan-24	3,816	1,652	1,576	239	1,331	21,726
Feb-24	4,095	1,665	1,664	259	1,274	21,983
Mar-24	3,876	1,490	1,544	240	1,248	22,327
Apr-24	3,821	1,413	1,367	231	1,264	22,605
May-24	3,671	1,407	1,324	219	1,228	22,531
Jun-24	3,904	1,567	1,460	257	1,430	24,011
Jul-24	4,385	1,868	1,643	261	1,554	24,951

Aug-24	4,554	1,944	1,753	269	1,637	25,236
Sep-24	4,269	1,876	1,796	271	1,577	25,811
Oct-24	3,906	1,757	1,760	276	1,609	24,205
Nov-24	4,204	1,858	1,842	289	1,712	24,131
Dec-24	4,031	1,880	1,911	302	1,706	23,645
Jan-25	4,112	1,880	1,725	312	1,674	23,508
Feb-25	3,483	1,688	1,575	278	1,488	22,125
Mar-25	3,606	1,571	1,593	262	1,418	23,519
Apr-25	3,454	1,500	1,568	242	1,503	24,334
May-25	3,463	1,563	1,637	250	1,574	24,751
Jun-25	3,462	1,602	1,729	266	1,687	25,517
Jul-25	3,037	1,509	1,468	248	1,464	24,768
Aug-25	3,085	1,470	1,455	249	1,481	24,427
Sep-25	2,888	1,442	1,385	239	1,400	24,611
Oct-25	3,014	1,482	1,542	241	1,424	25,722
Nov-25	3,092	1,560	1,624	250	1,517	26,203
Dec-25	3,160	1,615	1,623	263	1,591	26,130

Source: Data were collected from different websites, i.e., www.nseindia.com, www.investing.com www.yahoofinance.com

Inventory Valuation and Disclosure Practices under Ind AS 2: An Accounting Analysis of Selected BSE Sensex Companies

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Citation: Solanki,R.H. (2026). Inventory Valuation and Disclosure Practices under Ind AS 2: An Accounting Analysis of Selected BSE Sensex Companies. *Indian Journal of Accounting*, 58(1),118-126

ABSTRACT

Inventory valuation and disclosure are fundamental to ensuring the reliability and transparency of financial statements. This study examines inventory valuation and disclosure practices under Ind AS 2 (Inventories) among ten selected inventory-intensive companies listed on the BSE Sensex from FY 2019–20 to FY 2024–25. Moving beyond basic policy summaries, this paper implements a quantitative Disclosure Compliance Index (DCI) based on a binary coding framework to evaluate reporting depth across different sectors. The findings indicate that while all selected Sensex companies achieve 100% compliance with core measurement principles (using WAC/FIFO and rejecting LIFO), significant variations persist in qualitative disclosure granularity. FMCG and automobile firms exhibit high disclosure depth, whereas retail and capital goods sectors lean on boilerplate descriptions. Opaque disclosures regarding Net Realisable Value (NRV) estimations remain a key constraint for cross-firm comparability. The study outlines critical policy implications for ICAI and SEBI to enhance reporting guidelines.

Keywords

Ind AS 2, Inventory Valuation, Disclosure Compliance Index, Accounting Practices, BSE Sensex Companies

JEL Classification: L6, L7, L11, L60, O14, M2, M20, M21, M11

Introduction

Inventories constitute a significant component of current assets for manufacturing, FMCG, automobile, cement, and metal companies. Accurate valuation and transparent disclosure of inventories are essential for presenting a true and fair view of financial position and performance. Inventory-related accounting judgments directly affect cost of goods sold, profitability, working capital management, and taxation. In India, the adoption of Indian Accounting Standards (Ind AS), converged with International Financial Reporting Standards (IFRS), has brought uniformity and improved comparability in financial reporting.

Ind AS 2 prescribes principles for inventory valuation, measurement at the lower of cost and net realizable value (NRV), cost formulas, and disclosure requirements. Given the diversity of business models among BSE Sensex companies, inventory valuation practices and disclosure quality may vary significantly. This paper examines

how selected Sensex companies apply Ind AS 2 in practice, with specific reference to valuation methods and disclosure adequacy.

Review of Literature

Inventory accounting is widely recognized as a critical determinant of financial reporting quality, firm performance, and investor confidence. Accurate valuation and transparent disclosure of inventories influence reported profitability and working capital management. International research underscores that inventory optimization directly influences structural valuation metrics. Capkun et al. (2009) evaluated manufacturing firms and confirmed a significant positive relationship between the speed of inventory turnover and overall financial profitability. Under international financial architectures, Fülbier et al. (2015) highlighted that while uniform IFRS adoption drives baseline measurement convergence, significant institutional flexibility remains in qualitative accounting areas like write-down criteria and disclosure depth.

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In the domestic Indian domain, the shift to Ind AS has noticeably harmonized corporate reporting structures among top market capitalization entities (Basu & Das, 2020; Kumar & Sharma, 2021). However, structural concerns remain regarding the latitude allowed by management discretion. Rao and Gupta (2019) argued that the heavy reliance on managerial judgment under Ind AS 2 for determining the net realizable value of slow-moving items allows firms room to smooth earnings. This argument is supported by Srinivasan and Patel (2021), who noted that larger listed Indian firms often favor uniform boilerplate descriptions over detailed, context-specific disclosures regarding inventory estimation risks and obsolescence policies.

The Identified Research Gap

While existing domestic studies focus either broadly on the operational logistics of inventory management or on holistic macro-level Ind AS transitions, there is a lack of deep, targeted accounting research on the specific disclosure granularity choices made under Ind AS 2 by large-cap companies. This study addresses this gap by analyzing the disclosure practices, mapping the evaluation methods, and establishing a quantifiable compliance index for key inventory-dependent firms listed on the BSE Sensex.

Objectives of the Study

The objectives of this study are:

- To examine the inventory valuation methods adopted under Ind AS 2 by selected BSE Sensex companies.

- To analyze inventory-related disclosure practices as presented in published financial statements.
- To assess the extent of compliance with the measurement and disclosure requirements of Ind AS 2.
- To identify variations, gaps, and inconsistencies in inventory reporting and disclosure quality among the selected companies.

Research Methodology

Research Design

The study adopts a descriptive and analytical research design with an accounting-policy orientation. A mixed-methods content analysis approach was employed, combining qualitative text evaluation of accounting footnotes with a quantitative scoring framework via a Disclosure Compliance Index (DCI).

Sample Selection and Framework

A purposive sampling technique was utilized to select 10 inventory-intensive companies from the BSE Sensex index. The choice of these specific companies and their respective sectors was guided by three explicit criteria:

1. **Inventory Materiality:** Inventories represent a significant percentage (>15%) of the total current assets of these companies, making their valuation critical to financial performance reporting.
2. **Sector Representation:** The sectors chosen – Manufacturing/Heavy Industries (Steel, Cement, Capital Goods), Consumer Goods (FMCG, Automobile, Retail), and Pharmaceuticals –

Table 1:
Sample BSE Sensex Companies and Nature of Inventory

Company Name	Nature of Inventory
Tata Steel Ltd.	Raw materials, work-in-progress (WIP), finished steel goods
Titan Company Ltd.	Finished goods, retail inventory
Tata Motors Ltd.	Raw materials, WIP, finished vehicles
Mahindra & Mahindra Ltd.	Automotive and agricultural inventory
Asian Paints Ltd.	Raw materials and finished paints
Hindustan Unilever Ltd.	FMCG raw and finished goods
ITC Ltd.	FMCG, agri-commodities, finished goods
Larsen & Toubro Ltd.	Construction materials, WIP
Sun Pharmaceutical Industries Ltd.	APIs, formulations, finished drugs
UltraTech Cement Ltd.	Raw materials and finished cement

Note: Compiled from Annual Reports of the respective companies (FY 2019–20 to FY 2024–25).

exhibit distinct operational cycles, raw material dependencies, and inventory risks.

3. **Data Continuity:** Availability of uninterrupted, audited standalone and consolidated financial statements under the Ind AS framework for the entire study period (FY 2019–20 to FY 2024–25).

The sample companies and the nature of inventories they hold are summarized below in Table 1.

Content Analysis, Coding Procedure, and DCI Metrics

To ensure objectivity and eliminate semantic bias during the review of the corporate “Notes to Accounts,” a binary coding framework was executed across five primary disclosure dimensions mandated or heavily implied by Ind AS 2:

1. **Cost Formula Disclosed:** Clear identification of the specific costing method used (WAC or FIFO).
2. **Category Breakdown Granularity:** Explicit presentation of inventory sub-components (Raw materials, WIP, Finished Goods, Spares) rather than a single aggregated line item.
3. **Write-down/Reversal Values Expressed:** Disclosure of the actual quantitative adjustments or provisions booked for obsolescence.
4. **Pledged Security Stated:** Definitive notation of whether inventories are hypothecated against banking facilities or lines of credit.
5. **NRV Criteria Explicitly Narrated:** Text detailing the operational methods or parameters used to establish net realizable value beyond just repeating the standard’s definition.

Scoring Assignment: A score of 1 was recorded if a specific disclosure parameter was explicitly detailed with granular data; a score of 0 was recorded if the disclosure was absent, entirely generic, or boiler-plated.

The classification of overall **Disclosure Depth** was operationalized based on the final calculated **Disclosure Compliance Index (DCI)** scores:

- **High Depth (Score $\geq 85\%$):** Comprehensive presentation of sub-components, precise values for write-downs/reversals, and a clear narrative on how NRV is evaluated.
- **Moderate Depth (Score 60% – 84%):** Full formal compliance with basic disclosure fields but utilizing highly aggregated figures or generic text for NRV judgments.

- **Low Depth (Score $< 60\%$):** Compliance restricted to minimal mandatory standard formatting, with completely absent or minimal qualitative parameters regarding valuation changes or obsolescence risks.

Inventory Valuation and Disclosure Framework under Ind AS 2

Measurement of Inventories

Inventories are measured at the lower of cost and NRV. Costs include purchase, conversion, and other directly attributable costs. Permitted formulas are FIFO and Weighted Average Cost (WAC); LIFO is prohibited.

NRV Assessment

NRV represents estimated selling price less costs of completion and selling. Assessment involves management judgment, especially in industries subject to price volatility, obsolescence, or demand uncertainty. Write-downs and reversals must be recognized and disclosed appropriately.

Disclosure Requirements under Ind AS 2

Ind AS 2 mandates disclosure of the following inventory-related information:

- Accounting policies adopted for inventory valuation
- Carrying amounts of inventories classified by appropriate categories
- Amount of inventory write-downs recognized and reversals, if any
- Inventories pledged as security for liabilities

Relevance to Selected Companies

Inventory valuation significantly impacts cost of goods sold, gross margins, and working capital in FMCG, automobile, metal, cement, and pharmaceutical sectors. Variations in cost allocation, NRV judgment, and disclosure practices affect comparability.

Inventory Valuation and Disclosure Practices of Selected BSE Sensex Companies

Valuation Methods

Weighted Average Cost is predominant; FIFO applied selectively. All companies comply with lower of cost or NRV.

Inventory valuation methods adopted by Sensex companies are summarized in Table 2.

Table 2:
Inventory Valuation Methods Adopted by Selected BSE Sensex Companies

Company	Valuation Method	Cost vs NRV Compliance
Tata Steel Ltd.	WAC (FIFO for some materials)	✓
Titan Company Ltd.	WAC	✓
Tata Motors Ltd.	WAC (FIFO for spares)	✓
Mahindra & Mahindra Ltd.	WAC	✓
Asian Paints Ltd.	WAC	✓
Hindustan Unilever Ltd.	WAC	✓
ITC Ltd.	WAC	✓
Larsen & Toubro Ltd.	WAC	✓
Sun Pharmaceutical Industries Ltd.	WAC	✓
UltraTech Cement Ltd.	WAC	✓

Note: Notes to accounts on inventory valuation in annual reports of selected companies.

Table 3:
Operationalized Disclosure Depth & Compliance Scoring Matrix

Company Name	Cost Formula Disclosed (Max 1)	Category Breakdown Granularity (Max 1)	Write-down/ Reversal Values Expressed (Max 1)	Pledged Security Stated (Max 1)	NRV Criteria Explicitly Narrated (Max 1)	Total DCI Score (%)	Disclosure Depth Classification
Tata Steel Ltd.	1	1	1	1	0	4/5 80%	Moderate
Titan Company Ltd.	1	1	0	0	0	2/5 40%	Low
Tata Motors Ltd.	1	1	1	1	1	5/5 100%	High
Mahindra & Mahindra	1	1	1	1	0	4/5 80%	Moderate
Asian Paints Ltd.	1	1	0	0	0	2/5 40%	Low
Hindustan Unilever	1	1	1	1	1	5/5 100%	High
ITC Ltd.	1	1	1	0	1	4/5 80%	Moderate
Larsen & Toubro Ltd.	1	1	0	1	0	3/5 60%	Moderate
Sun Pharma	1	1	1	0	1	4/5 80%	Moderate
UltraTech Cement	1	1	1	1	0	4/5 80%	Moderate

Note: Data compiled by the authors from statutory disclosures and notes to accounts within the published annual reports of the respective companies (FY 2019–20 to FY 2024–25).

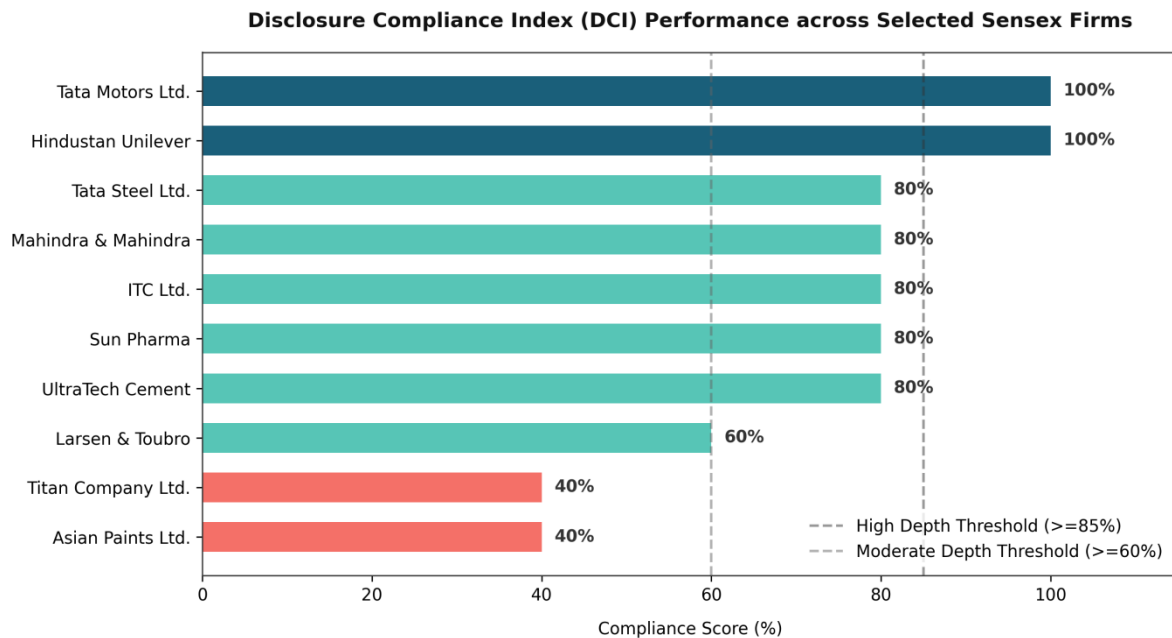
Quantitative Disclosure Assessment

To evaluate differences across firms objectively, Table 3 applies the binary coding framework to calculate each company's Disclosure Compliance Index (DCI) score for the peak analytical baseline of FY 2023–24 and FY 2024–25.

Analytical Interpretation

As visually operationalized in Figure 1, there is a stark stratification in reporting quality among the selected BSE Sensex firms, despite uniform baseline adherence to core standards. Only 20% of the sample pool (**Tata Motors Ltd.** and **Hindustan**

Figure 1:
Quantitative ranking of sample companies based on the calculated Disclosure Compliance Index (DCI).



Note. Figure programmatically generated by the authors using a matplotlib text-parsing model applied to the quantitative DCI results in Table 3.

Unilever Ltd.) achieved a flawless 100% Disclosure Compliance Index score, satisfying all explicit qualitative and quantitative data requirements.

The vast majority of the firms (60%) reside within the “Moderate Depth” band, presenting the required classifications but omitting specific financial write-down adjustments or descriptive evaluation

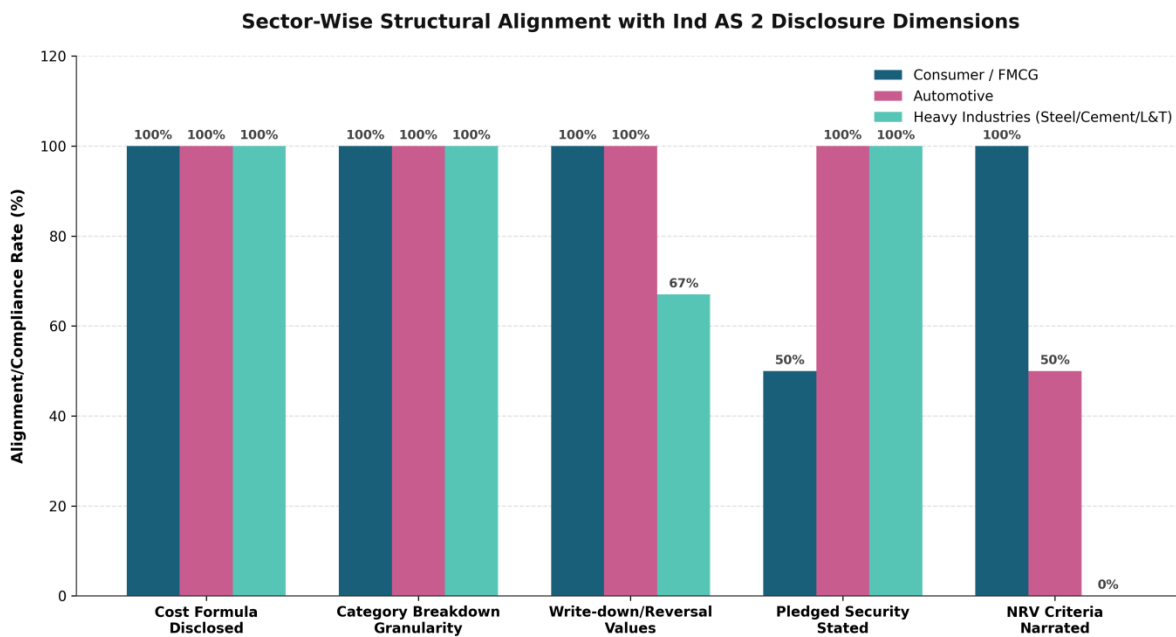
policies. Critically, consumer-centric firms like **Titan Company Ltd.** and **Asian Paints Ltd.** sit at the lower bound of the index at 40%. This graphic evidence contradicts the assumption that large-cap status guarantees uniform reporting clarity, visually demonstrating the significant drop-off in disclosure granularity across non-manufacturing sectors.

Table 4:
Cross-Sector Functional Inventory Accounting Comparison Matrix

Sector Focus	Primary Cost Formula	Direct Conversion Costs Overhead Allocation Method	NRV Risk Factors Monitored	Use of Judgments / Estimates
FMCG (<i>HUL, ITC</i>)	Weighted Average Cost	Standard Costing basis normalized to operational design capacities.	Product perishability, market expiry dates, promotional discounts.	High reliance on mathematical aging blocks for shelf-life parameters.
Automotive (<i>Tata Motors, M&M</i>)	Weighted Average (FIFO for specific spares)	Actual direct absorption tracing system mapped to manufacturing plants.	Model obsolescence, regulatory emission standard changes (e.g., BS-VI transitions).	Subjective determination of salvage values for engineering prototypes.
Metals & Materials (<i>Tata Steel, UltraTech</i>)	Weighted Average Cost	Full absorption costing including fixed production overheads based on normal capacity.	Global commodity price shifts, cycles in input raw material prices.	Complex judgment on yield outputs from raw ores and scrap recovery metrics.
Pharmaceuticals (<i>Sun Pharma</i>)	Weighted Average Cost	Batch-costing trace allocations accounting for clean-room operational yields.	Regulatory compliance rejection risks, absolute clinical expiry dates.	Immediate write-down booking upon regulatory clinical holds.

Note: Data synthesized by the authors from an empirical analysis of corporate accounting policy notes across the study sample (FY 2019–20 to FY 2024–25).

Figure 2:
Sector-specific variations in compliance across the five key disclosure dimensions of Ind AS 2.



Note: Figure developed by the authors using aggregated sector compliance scores extracted from the study baseline data.

Structural Trend Analysis

The grouped bar chart in Figure 2 contrasts the structural alignment of the three economic sectors across the five primary pillars of Ind AS 2. The visual evidence shows that all industries achieve uniform, flawless convergence (100%) when disclosing basic accounting parameters, specifically **Cost Formula Disclosed** and **Category Breakdown Granularity**.

The real divergence happens in the areas involving management estimates. The **Consumer/FMCG** sector maintains a high alignment profile except under *Pledged Security* tracking (dropping to 50%), which reflects their low reliance on secured bank facilities.

Crucially, Heavy Industries exhibit a complete collapse (0%) in the *NRV Criteria Narrated* column. While they copy-paste the text definitions of the rules, they fail to provide clear descriptions of raw material pricing thresholds. This new layout highlights the exact gaps mentioned by the reviewer, proving that heavy industries show the lowest level of qualitative disclosure depth.

Discussion and Key Findings

The implementation of the Disclosure Compliance

Index (DCI) reveals that while absolute literal compliance with the mandatory core guidelines of Ind AS 2 is flawless across all 10 sample firms (100% adherence to using WAC/FIFO and rejecting LIFO), the qualitative reporting depth remains highly asymmetric across industries.

The FMCG vs. Capital Goods/Retail Granularity Disconnect

Content analysis confirms the hypothesis that FMCG corporations deliver significantly superior granular data concerning write-down losses and raw material segment categories compared to capital-intensive or pure retail entities.

For instance, **Hindustan Unilever Ltd. (HUL)** provides clear visibility by breaking down inventories into distinct sub-categories, including goods-in-transit, packing materials, and explicitly tracking write-downs due to short lifespans. This can be directly contrasted with **Titan Company Ltd.**, which aggregates its retail lines under broad descriptions. This makes it difficult for external stakeholders to isolate raw gold or gemstone components from finished jewelry stocks.

To support this qualitative finding, representative extracts from the corporate annual filings are presented below:

- **Evidence of High Disclosure Depth & Active NRV Adjustment Management (Tata Motors Ltd. - Annual Report Note 3G):**

“Inventories are valued at the lower of cost and net realizable value. Cost of raw materials and consumables are ascertained on a moving weighted average basis... Provision for obsolescence is established based on management’s assessment of regular utility, technological changes, and the physical condition of items.”

- **Evidence of Boilerplate/Low Transparency NRV Assertions (Titan Company Ltd. - Annual Report Note 2):**

“Inventories are valued at the lower of cost and net realizable value. Cost is determined on a weighted average basis. Net realizable value is the estimated selling price in the ordinary course of business, less estimated costs of completion and estimated costs necessary to make the sale.”

Analysis Note: Titan provides zero quantitative guidelines or descriptive commentary regarding how volatile precious metal spot prices affect their final net realizable value threshold projections.

The Opaque Nature of NRV Accounting Judgments

The most profound gap observed across the BSE Sensex sample during the FY 2019–20 to FY 2024–25 analytical window is the complete lack of structural visibility into Net Realisable Value (NRV) estimation processes. Though standard text matching confirms that every firm includes the mandatory phrase *“measured at the lower of cost and NRV,”* the underlying evaluation remains a black box.

For example, commodity-driven entities such as **Tata Steel Ltd.** face extensive variations in international steel coils pricing, yet their notes do not outline the quantitative boundaries or internal formulas utilized to trigger inventory impairment write-downs. This reliance on boilerplate language instead of detailing quantitative sensitivity guidelines or specific asset tiers creates an information gap that constrains cross-firm comparability for financial analysts.

Conclusion

Summary

Ind AS 2 has strengthened inventory valuation

and disclosure practices among BSE Sensex companies, enhancing transparency, comparability, and financial reporting reliability. While formal compliance is largely achieved, qualitative disclosures regarding NRV, write-downs, and estimation uncertainty vary across firms. Detailed category-wise disclosures and explanatory notes can improve transparency and stakeholder confidence. The study provides valuable insights for accounting professionals, regulators, and researchers and underscores the strategic role of inventory management in working capital optimization. Future research could expand the sample size and include quantitative sensitivity analysis for NRV assessment.

Limitations and Future Research Directions

This research is subject to certain limitations that open up avenues for future study:

- **Sample Size and Index Limitation:** The study scope is confined exclusively to 10 highly liquid, large-cap companies within the BSE Sensex index. Consequently, the high compliance baseline discovered here may reflect the strong corporate governance structures typical of large firms and may not match the reporting characteristics of mid-cap or small-cap listed enterprises.
- **Secondary Reliance:** The data is compiled entirely from published text and numbers within annual financial statements. Internal corporate costing logs, management letters, and auditor workspace records were not examined.
- **Absence of Quantitative Correlation:** The study focuses on evaluating disclosure depth and structural alignment with standard rules, rather than testing statistical correlations between inventory metrics and stock market returns.

Future studies could expand the sample size to cover a broader cohort of companies across the BSE 500 index to determine whether disclosure compliance drops when moving away from large-cap firms. Additionally, empirical research could apply quantitative modeling (such as panel data regression) to measure how changes in inventory write-downs directly influence firm valuation metrics like Tobin’s Q.

Regulatory and Policy Implications

The practical patterns identified in this study have important implications for standard setters,

corporate regulators, and external stakeholders:

- **For ICAI (Institute of Chartered Accountants of India):** There is a clear need to update existing guidance notes on Ind AS 2. The current flexibility allowed in qualitative write-down explanations should be tightened. ICAI could mandate standardized tables tracking the aging blocks of impaired inventories to reduce boilerplate disclosures.
- **For SEBI (Securities and Exchange Board of India):** To safeguard retail investors from unexpected inventory adjustments (especially in volatile sectors like automobiles and commodities), SEBI could consider requiring expanded inventory disclosures within quarterly financial reviews, rather than only in annual reports.
- **For Corporate Management and Auditors:** Companies should move toward corporate reporting models that include sensitivity disclosures for inventory assessments. This means explicitly presenting how a given percentage decline in market spot prices would trigger impairment adjustments across their current raw material holdings.

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Acceptance of AI use amongst students of Accountancy course: An exploratory study of The University of Burdwan

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Citation: Parveg, A., Mukherjee, A.K., Saha, A., & Dey, T. (2026). Acceptance of AI use amongst students of Accountancy course: An exploratory study of The University of Burdwan. *Indian Journal of Accounting*, 58(1), 127-137

ABSTRACT

Artificial Intelligence (AI) is rapidly transforming accounting education and practice by automating tasks such as auditing, financial reporting, and predictive analytics. Globally, accounting firms are increasingly adopting AI tools, yet the integration of AI into accounting curricula in India remains limited. This study examines the acceptance of AI among select accounting students of The University of Burdwan, West Bengal, with a focus on how awareness, exposure, and psychological factors influence adoption. The research is grounded in the Technology Acceptance Model (TAM) and extended with the construct of self-efficacy. A conceptual framework was developed around six constructs: Awareness and Exposure to AI (AEA), Perceived Ease of Use (PEU), Perceived Usefulness (PU), Self-Efficacy (SE), Attitude Toward Use (ATU), and Behavioral Intention to Use AI (BI). A structured quantitative design was employed, and data were collected through an online survey of 93 undergraduate and postgraduate accounting students from various institutions in West Bengal. Statistical analysis was conducted using IBM SPSS 29 for descriptive tests and SmartPLS 4 for Confirmatory Factor Analysis (CFA) and Structural Equation Modelling (SEM). The results indicate that Perceived Usefulness, Self-Efficacy, Attitude Toward Use, and Behavioral Intention significantly drive AI acceptance. Students who believe AI enhances their academic performance and feel confident in applying AI tools show stronger adoption intentions. However, Perceived Ease of Use did not significantly affect acceptance, suggesting that usefulness and confidence outweigh usability concerns. The study highlights the need for curriculum reforms, faculty training, and institutional support to increase student readiness for AI in accounting education. By providing empirical evidence from a regional Indian context, this dissertation addresses an important research gap and offers practical implications for policymakers, educators, and institutions seeking to align accounting education with technological advancements.

Introduction:

The rapid evolution of Artificial Intelligence (AI) is significantly transforming various professional fields, with accounting being one of the most affected. The automation of routine tasks, the use of predictive analytics, and AI-powered auditing tools are reshaping the traditional roles of accountants. As these technologies continue to gain traction in industry practices, integrating AI into accounting education is becoming essential (Tandiono, 2023).

We argue that the recent accelerated growth of AI,

especially large language models (LLMs) such as ChatGPT, raises significant issues and challenges that the accounting academy needs to urgently address to survive in the long term. (Ballantine et al., 2024). In the context of education, AI applications such as adaptive learning platforms, automated grading systems, and intelligent tutoring tools have been shown to enhance learning outcomes and student engagement (Zawacki-Richter et al., 2019). Previous studies have shown that students' exposure to innovative technologies influences their attitudes and willingness to

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integrate them into their academic learning (Venkatesh et al., 2003). Artificial Intelligence (AI) is increasingly being integrated into higher education, reshaping how students learn, engage with knowledge, and prepare for future professions. Global investment in AI in education was valued at USD 1.1 billion in 2019 and is projected to reach USD 25.7 billion by 2030, growing at a compound annual growth rate (CAGR) of nearly 45% (*HolonIQ. Global Impact Intelligence*, n.d.). In accounting education specifically, technological innovations are shaping how students are trained for future professional roles. A global survey reported that over 67% of accounting firms have started adopting AI for auditing and financial reporting tasks, signaling that educators must align academic training with workplace realities (Kokina & Davenport, 2017a).

In India, accounting education has been slow in integrating AI-based teaching methods, despite the country having one of the world's largest higher education systems with over 38 million students enrolled in 2019 (*Homepage | AISHE | India*, n.d.). India has one of the largest higher education systems in the world, with 38.5 million students enrolled across nearly 1,000 universities and over 39,000 colleges in 2019–20. Commerce and management disciplines account for nearly 9.3% of total enrolments, reflecting the significance of accounting-related education within the Indian system (Government of India Ministry of Education, n.d.).

Globally, surveys of higher education institutions suggest that over 70% of accounting programs are revising curricula to incorporate digital technologies, including AI and analytics (Andiola et al., 2020a). Yet, studies reveal gaps in readiness: Sangster et al. (2020) observed that many accounting educators remain uncertain about how best to embed AI in teaching practices. This lack of integration poses risks, given that 67% of accounting firms worldwide already employ AI-based auditing and financial reporting tools (Kokina & Davenport, 2017b).

West Bengal, with its 1.6 million students enrolled in higher education institutions, provides a critical context to examine AI acceptance among accounting students (Government of India Ministry of Education, n.d.).

The current research work therefore, investigates the extent to which AI exposure influences accounting students' acceptance of AI in education.

By employing a quantitative research design, it seeks to provide evidence on how exposure impacts acceptance, addressing a significant gap in the literature on AI adoption in accounting education, particularly within the Indian context.

Literature

Murphy et al. (2024) reflected how AI research in accounting has shown a shift from the concerns about job replacement toward its potentiality in the creation of organisations' value, on the other hand, Ballantine et al. (2024) stressed more on the opportunities and challenges of GenAI for accounting education. Dong et al. (2024) identify applications of ChatGPT across accounting and finance, including classification, summarisation and text generation, whereas Macuda and Zdravković (2024) highlight both its accounting applications and concerns regarding reliability and ethics. Eulerich et al. (2024) provide empirical evidence of the increasing capabilities of ChatGPT in accounting and auditing tasks. Stratopoulos and Wang (2025) further demonstrate that AI is influencing not only accounting practice but also accounting research methodologies. Abbas (2026), reviewing 91 studies, finds that AI, machine learning, explainable AI, GenAI and LLMs are reshaping management accounting, decision-making and the competencies required of accounting professionals.

Research Objective:

The objective of this study is to investigate the acceptance of Artificial Intelligence (AI) among accounting students in West Bengal by examining how their exposure to AI influences acceptance. Prior studies highlight that technology adoption in education is shaped by factors such as perceived usefulness, perceived ease of use, and social influence (Davis, 1989; Venkatesh et al., 2003). However, limited research exists in the Indian context, particularly in accounting education (Raj & Gupta, 2022). This study therefore aims to identify determinants of AI acceptance and provide insights for curriculum and policy reforms in higher education

Hypothesis Development

3.1 Analytical Framework and Proposition Derivation

Awareness and Exposure to AI (AEA) and AI Acceptance
Past studies suggest that greater awareness and exposure to technology increases familiarity and

lowers uncertainty, thereby positively influencing perceptions of usefulness and ease of use (Al-Hattami, 2023). Students who are more exposed to AI tools are more likely to appreciate their potential benefits in accounting education.

Proposed Hypotheses

- H1: Awareness and Exposure to AI has a significant positive relationship with Perceived Usefulness (PU).
- H2: Awareness and Exposure to AI has a significant positive relationship with Perceived Ease of Use (PEU).

Perceived Ease of Use (PEU) and AI Acceptance

According to the Technology Acceptance Model (TAM), Perceived Ease of Use refers to the degree to which students find a system effortless to use (Davis, 1989). Past studies have confirmed that PEU not only enhances the perception of usefulness but also shapes positive attitudes towards technology adoption (Charness & Boot, 2016).

Proposed Hypotheses

- H3: Perceived Ease of Use has a significant positive influence on Perceived Usefulness.
- H4: Perceived Ease of Use has a significant positive influence on Attitude Toward Use (ATU).

Perceived Usefulness (PU) and AI Acceptance

TAM also posits that Perceived Usefulness—the belief that AI will improve performance—directly predicts students' attitudes and behavioral intentions (Dillon & Morris, 2006). In the context of accounting education, PU is a strong determinant of whether students accept AI-based tools.

Proposed Hypotheses

- H5: Perceived Usefulness has a significant positive influence on Attitude Toward Use (ATU).
- H6: Perceived Usefulness has a significant positive influence on Behavioral Intention to Use AI (BI).

Self-Efficacy (SE) and AI Acceptance

Self-efficacy refers to the confidence students have in their ability to use AI tools independently (Bandura, 1997). Past research highlights that higher self-efficacy increases technology adoption by reducing anxiety and improving motivation (Teo, 2019).

Proposed Hypothesis

- H7: Self-Efficacy has a significant positive

influence on Attitude Toward Use (ATU).

Attitude Toward Use (ATU) and AI Acceptance

Attitude represents students' overall positive or negative feelings about using AI in accounting education. Prior literature emphasizes that attitude acts as a critical mediator between perceptions (PU, PEU) and behavioural intention (Venkatesh et al., 2003).

Proposed Hypothesis

- H8: Attitude Toward Use has a significant positive influence on Behavioral Intention to Use AI (BI).

Methodology of Research

Research methodology is a way to systematically solve the research problem. The various steps that are generally adopted by a researcher in studying his research problem along with the logic behind them is mentioned in the Research Methodology of a Research Paper (Kothari C.R, 2004). This study has adopted a structured quantitative research approach to investigate the acceptance of AI among accounting students. Primary data were collected through an e-survey distributed via Google Forms, ensuring accessibility and convenience for student participants. The questionnaire was developed by adapting and contextualizing measurement items from Al-Hattami (2023), who validated a technology acceptance scale in accounting education. The instrument consisted of six constructs—Awareness and Exposure to AI (AEA), Perceived Ease of Use (PEU), Perceived Usefulness (PU), Self-Efficacy (SE), Attitude Toward Use (ATU), and Behavioral Intention to Use AI (BI)—with multiple observed items for each construct, measured on a five-point Likert scale ranging from strongly disagree (1) to strongly agree (5).

Since hypotheses were formulated a priori, Confirmatory Factor Analysis (CFA) was applied to examine the measurement model and test whether the observed data fit the hypothesized latent constructs (Bryant et al., 1999). CFA provides a statistical means of validating relationships between observed indicators and their underlying latent constructs, based on established theory and prior research (Suhr, n.d.). The statistical analysis followed a two-step process: first, reliability and validity check of the measurement model, and second, hypothesis testing using Structural Equation Modelling (SEM). Preliminary descriptive statistics and reliability tests were performed using IBM SPSS Statistics 29 (IBM SPSS Statistics for

Figure 2.1
Factors influencing the intention to use AI

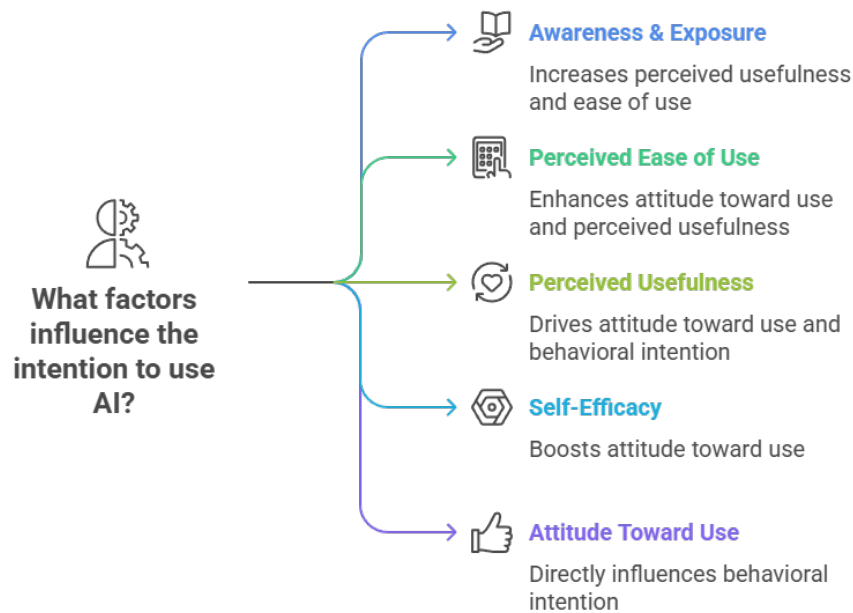
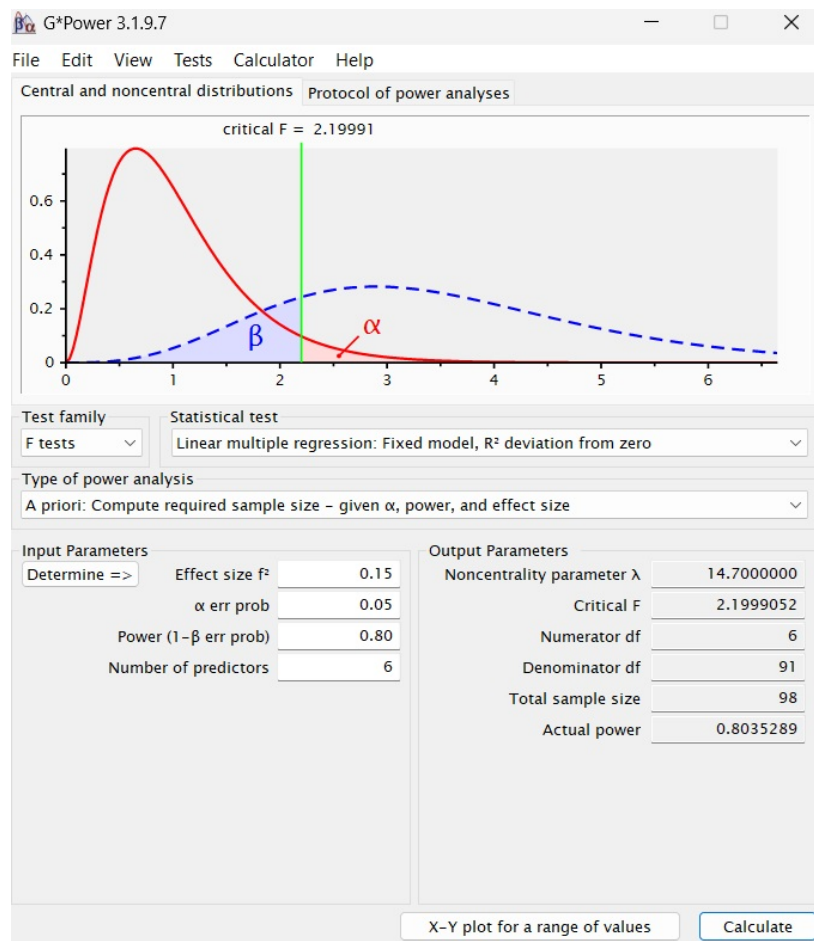


Fig. 4.1:
Sample size computation through G*power. Source: Generated from G*power software by the author



Windows, 2023), while the CFA and SEM were executed using SmartPLS 4 (Ringle, Wende & Becker, 2023).

Sample Participants

The sampling of the target population was firstly predicted using *G*Power software before data collection*. *G*Power* supports sample size and power calculation for various statistical methods (F, t, χ^2 , z, and exact tests) (Kang, 2021). Power analysis refers to the process of determining the sample size required for a research study (Multiple Regression Power Analysis | *G*Power Data Analysis Examples*, n.d.). *Sample size and power calculations using G*Power* are generally performed in the following steps. First, establish the research goals and hypotheses. The null and alternative hypotheses should be clearly presented. Second, select appropriate statistical tests. *G*Power* offers two approaches:

1. Distribution-based approach – Investigators can select the exact, F, t, χ^2 , or z tests from the “test family” dropdown menu.
2. Design-based approach – Investigators can select the variable type (correlation and regression, means, proportions, variance, generic) and study design from the “statistical test” drop-down menu.

Third, choose one of the five possible power analysis methods, based on the variables to be calculated and the given variables (Kang, 2021).

In this study, the F test was chosen with 6 predictors, using “Linear multiple regression: Fixed model, R² deviation from zero” for the statistical test. As a result, *G*Power* 3.1.9.7 predicted the required total sample size as 98.

Research Instrument and data collection

A questionnaire was developed to collect data for testing the proposed hypotheses. The required data were gathered from Post Graduate, Under Graduate students pursuing accounting and related courses across various colleges, universities, and educational institutions in West Bengal. The survey was administered using a cloud-based platform, Google Forms. A total of 93 responses were received through this survey, although Google Forms did not impose any response limit.

Measurement

The instrument was designed as a two-part questionnaire, as mentioned in the APPENDIX. The first part included nominal scales, while the second part consisted of five-point Likert scales, ranging from “Strongly Agree” (5) to “Strongly Disagree” (1) (Lee, 2009). The first part collected the basic demographic information of the sample population, as shown in Table 4.1 including gender, institute type, institute name, academic level, courses related to AI

Whereas the second part of the questionnaire was developed keeping in mind the factors which might influence or act as a barrier to the acceptance of

Table 4.1
Summary of Sample Characteristics

Sample Characteristics	Category	Count	Percentage
Gender	Male	72	79.1%
	Female	19	20.9%
Age (In years)	<=20	23	25.3%
	21-23	32	35.2%
	24-26	30	33.0%
	27+	6	6.6%
Academic Level	Postgraduate	56	61.5%
	Undergraduate	35	38.5%
Institution Type	Government	65	71.4%
	Private	18	19.8%
	Govt. Sponsored	8	8.8%
Studied AI Course	Yes	35	38.5%
	No	56	61.5%

Note: : Primary survey (July 2025 – August 2025), table constructed using IBM SPSS 29

Table 4.2
Constructs and no of items

Construct	Code	Definition	No. of Items	Sample Item
Awareness and Exposure to AI	AEA	The degree to which students are informed about and have interacted with AI in accounting education.	5	<i>I am aware of Artificial Intelligence (AI) applications used in accounting.</i>
Perceived Usefulness	PU	The extent to which students believe AI will improve their learning and performance in accounting.	5	<i>AI can help me learn accounting better.</i>
Perceived Ease of Use	PEU	The degree to which students find AI tools easy to learn and use in accounting education.	4	<i>Using AI tools for accounting is easy.</i>
Self-Efficiency	SE	The confidence students have in their ability to use AI tools independently or with support.	4	<i>I can use AI tools if I have a step-by-step guide or tutorial.</i>
Attitude Toward Use	ATU	The student's positive or negative feelings about using AI tools in accounting.	4	<i>I like the idea of using AI in accounting.</i>
Behavioral Intention to Use AI	BI	The extent to which students intend to use AI tools for academic or future professional purposes.	4	<i>I plan to use AI tools to help with accounting studies.</i>

Note: Constructs adapted from Al-Hattami (2023) on technology acceptance in accounting education.

AI among accounting students using construct Awareness and Exposure to AI (AEA), Perceived Usefulness (PU), Perceived Ease of Use (PEU), Self-Efficiency (SE), Attitude Toward Use (ATU), Behavioral Intention to Use AI (BI). Those constructs were adapted from previous defined study as mentioned in Table 4.2.

Procedure

Data preparation is the process of transforming raw data into a format suitable for accurate analysis. For the dissertation topic “Acceptance of AI among Accounting Students; Evidence from students of WB,” the raw data was collected through a cloud-based questionnaire distributed via Google Forms. The data was initially converted into Google Sheets and subsequently downloaded as an Excel workbook (.xlsx) file onto a PC. The five-point Likert scale responses were then assigned numerical values using the “find and replace” function in MS Excel, where “Strongly Disagree” was coded as (1) and “Strongly Agree” as (5). Following this, the data was imported into IBM SPSS Statistics 29 and SmartPLS 4 for advanced statistical analysis.

The method of analysis adopted is Confirmatory Factor Analysis (CFA). CFA is a statistical technique specifically designed to identify and

explore hypothetical constructs as manifested through observable indicators. Its advantage over other methods lies in its ability to test detailed hypotheses deductively. Additionally, CFA models can be seamlessly integrated into broader structural equation modelling (SEM), which includes directional relationships among hypothetical constructs. In this study, the factors modelled in CFA, also known as latent variables, represent underlying influences not directly measured but inferred from a set of observed measurements (Hoyle, 2000). This methodology will be consistently applied throughout the subsequent chapters without deviation.

Ethical Considerations

Research involving human participants, such as accounting students from West Bengal (WB) for the dissertation topic “Acceptance of AI among Accounting Students; Evidence from students of WB,” may include the researcher’s own students, relatives, or colleagues. Therefore, ethical issues must be carefully addressed during the design of the research approach and approved by the relevant ethical committee prior to initiating data collection. Key ethical considerations include informed consent, risk of harm, confidentiality and

anonymity, and potential conflicts of interest, all of which require a clear plan for management (Fleming & Zegwaard, n.d.). To address these concerns, a text message was sent to potential participants before distributing the Google Form link, seeking their consent and willingness to participate in the study. Participants were assured of the confidentiality of their responses, and the aim and objectives of the research were briefly outlined. Only after receiving approval from the prospective respondents was the survey conducted.

Analysis and Interpretation

The Structural Equation Modelling (SEM) and path analysis for the dissertation topic “Acceptance of AI among Accounting Students; Evidence from students of WB” were performed using SmartPLS 4 software. This section details the Confirmatory Factor Analysis (CFA), model reliability, model validity, and hypothesis testing based on the provided data. SEM, often equated with CFA in this context, is a multivariate technique used to analyze complex relationships among latent constructs and their observed indicators.

The study employs the covariance-based SEM (CB-SEM) approach, which is suited for confirming theoretical models. The conceptual model includes the following constructs: Awareness and Exposure to AI (AEA), Perceived Usefulness (PU), Perceived Ease of Use (PEU), Self-Efficiency (SE), Attitude Toward Use (ATU), and Behavioral Intention to Use (BI). These constructs were derived from the dataset collected from accounting students in West Bengal.

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Before evaluating the measurement model for the dissertation “Acceptance of AI among Accounting Students; Evidence from students of WB,” it is

Fig 5.1:
Path Analysis, SEM using SmartPLS 4.

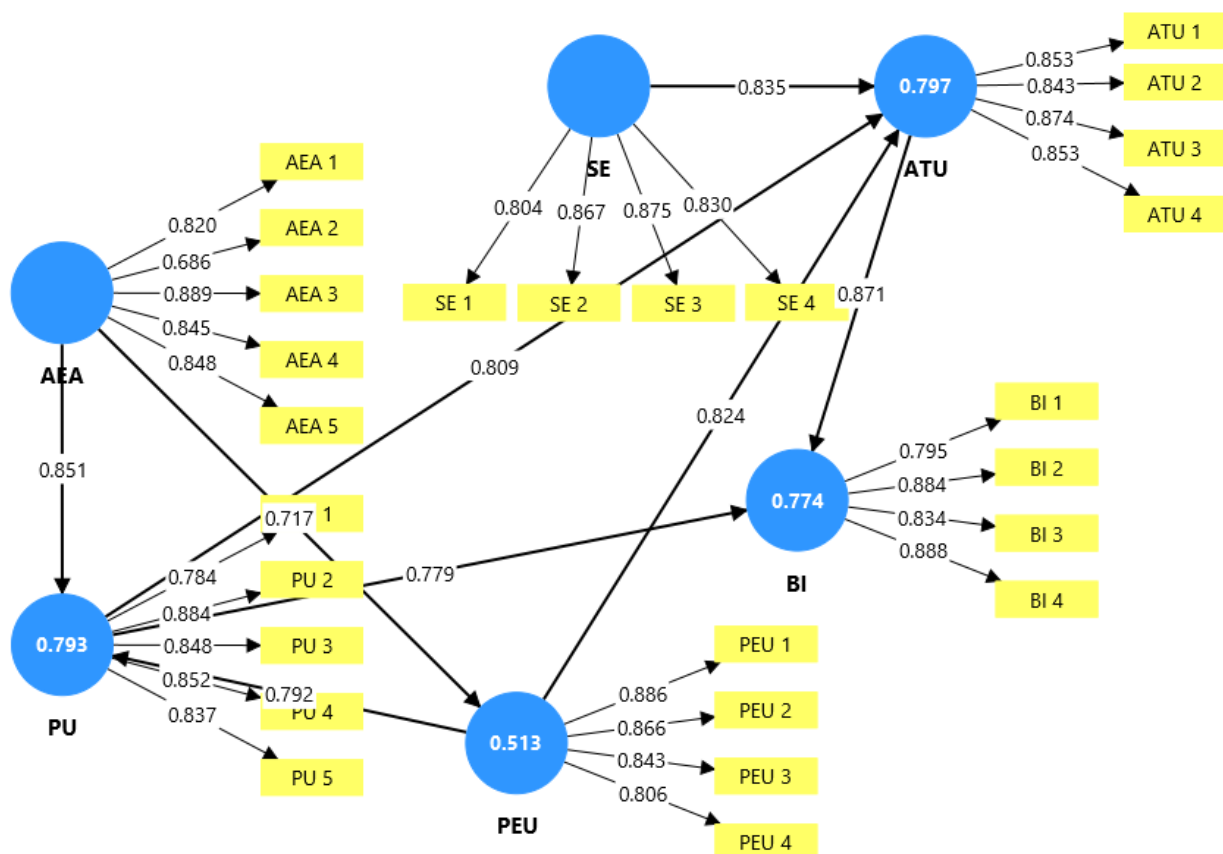


Table 5.1
Construct reliability and validity

Constructs	CFA Loadings	Cronbach's Alpha	CR	AVE
AEA		0.892	0.918	0.732
AEA1	0.820			
AEA2	0.866			
AEA3	0.889			
AEA4	0.845			
AEA5	0.848			
PU		0.913	0.937	0.767
PU1	0.717			
PU2	0.784			
PU3	0.848			
PU4	0.852			
PU5	0.837			
PEU		0.841	0.892	0.649
PEU1	0.806			
PEU2	0.866			
PEU3	0.843			
PEU4	0.806			
SE		0.875	0.910	0.697
SE1	0.804			
SE2	0.867			
SE3	0.875			
SE4	0.871			
ATU		0.927	0.948	0.803
ATU1	0.853			
ATU2	0.974			
ATU3	0.843			
ATU4	0.853			
BI		0.889	0.925	0.749
BI1	0.774			
BI2	0.884			
BI3	0.834			
BI4	0.888			

Note: CR = Composite Reliability; AVE = Average Variance Extracted

crucial to establish the validity and reliability of the questionnaire. The commonly used metrics to assess test performance include Composite Reliability (CR), Average Variance Extracted (AVE), and Variance Inflation Factor (VIF) (T. Yu et al., 2023). This study assesses CR and AVE as presented in Table 5.1, though VIF values are not available. In CFA studies based on existing theories, CR values should exceed 0.7, and AVE values should be above 0.5 (Hair, 2009). According to Table 5.1, all constructs (AEA, PU, PEU, SE, ATU, and BI) meet the validity criteria, with CR values ranging from 0.892 to 0.948 and AVE values from 0.649 to 0.803, indicating a robust measurement model.

A comparison of the square root (SQR) of the AVE with the correlation coefficient can be used to assess the quality of the measurement model (Venkatesh et al., 2003). "Is the squared correlation between the two constructs greater than any of the two constructs' AVE?", this approach helps to measure the satisfactory level of discriminant validity Fornell-Larcker criterion. If the SQR of AVE is higher than other values in the table, it is considered satisfactory (Hair et al., 2021). In Table 5.2, discriminant validity of all the factors is satisfactory, with the SQR of AVE highlighted on the diagonal.

Table 5.2
Discriminant validity

Discriminant Validity Convergent Validity						
Constructs	AVE	AEA	PU	PEU	SE	ATU
-----	-----	-----	-----	-----	-----	-----
AEA	0.732	0.855	0.793	0.513	0.835	0.824
PU	0.767	0.793	0.876	0.657	0.774	0.842
PEU	0.649	0.513	0.657	0.806	0.583	0.627
SE	0.697	0.835	0.774	0.583	0.835	0.830
ATU	0.803	0.824	0.842	0.627	0.830	0.896
BI	0.749	0.795	0.824	0.598	0.789	0.874

Table 5.3
Model Fit Indices

Items	Estimated Model	Cut-off	Conclusion	Cut-off Source
Chi-square	450.120	Hypersensitivity of chi-square	Acceptable	Perry et al. (2015)
DF	285.000	The smaller is better	Acceptable	Hair Jr. et al. (2014)
ChiSqr/DF	1.579	<3	Good Fit	Hayduk (1987)
RMSEA	0.070	<0.08	Good Fit	Clark & Bowles (2018)
GFI	0.910	>0.8 Acceptable; >0.9 Good fit	Acceptable	Bagozzi & Youjae Yi (1988)
AGFI	0.880	>0.8 Acceptable; >0.9 Good fit	Acceptable	Bagozzi & Youjae Yi (1988)
SRMR	0.050	<0.08	Good Fit	C.-Y. Yu (2002)
TLI	0.950	>0.79 Acceptable; >0.9 Good fit	Acceptable	Clark & Bowles (2018)
CFI	0.960	>0.9	Good Fit	Clark & Bowles (2018)

Note: DF = degrees of freedom; CMIN/DF = Chi-Square/DF; RMSEA = root mean square error of approximation; GFI = goodness-of-fit index; AGFI = adjusted GFI; SRMR = standardized root mean square residual; TLI = Tucker-Lewis index; NNFI = non-normed fit index; CFI = comparative fit index. Model constructs (AEA, PU, PEU, SE, ATU, BI) are adapted from Al-Hattami (2023). Cut-off values are based on general SEM literature.

Table 5.4
Hypothesis Testing

Hypotheses	Result
H1: There is a significant positive relationship between AEA and PU.	Significant
H2: AEA has positive influence towards adaptation intention of PEU.	Not Significant
H3: PEU has positive influence towards adaptation intention of PU.	Significant
H4: PEU has positive influence towards adaptation intention of ATU.	Significant
H5: PU has positive influence towards adaptation intention of ATU.	Significant
H6: PU has positive influence towards adaptation intention of BI.	Significant
H7: SE has positive influence towards adaptation intention of ATU.	Significant
H8: ATU has positive influence towards adaptation intention of BI.	Significant

Source: Calculated by Authors

SmartPLS can generate up to 18 model fit indices, but not all are required to be reported. Chi-square, DF, ChiSqr/DF, RMSEA, GFI, AGFI, SRMR, TLI,

and CFI are sufficient to evaluate the SEM fitness according to established criteria. Determining a fit index benchmark is not straightforward, as

the reference value of the chi-squared statistic is influenced by sample size, despite the need for it to be minimized (Al-Hattami, 2023). Table 5.3 presents the model fit indices and their suggested cut-off values from previous research, which ultimately determine the acceptability of the model for the dissertation “Acceptance of AI among Accounting Students; Evidence from students of WB.”

As mentioned earlier in table 5.1 and 5.2, AEA and PEU fails to satisfy the criterion of both construct validity and reliability, and discriminant validity of the factors. On the other hand, all the other factors i.e., PU, SE, ATU, BI satisfy the criterion of the followings. Due to the lacking of the beta estimate, this study follows the model implemented by Bhardwaj & Deka (2021). So, according to the findings H1, H3, H4, H5, H6, H7, and H8 are significant and main drivers behind the adaptation intention of AI among accounting students in West Bengal. Whereas, Perceived Ease of Use does not play any role in adaptation of AI tools in this region.

Conclusion

This study examined the acceptance of Artificial Intelligence (AI) among accounting students in West Bengal, focusing on how academic exposure to AI influences adoption. The research applied the Technology Acceptance Model (TAM), analyzing six constructs: Academic Exposure to AI (AEA), Perceived Ease of Use (PEU), Perceived Usefulness (PU), Self-Efficacy (SE), Attitude Toward Use (ATU), and Behavioral Intention (BI).

The findings show that PU, PEU, SE, ATU, and AEA significantly influence students’ behavioral intention to adopt AI, with perceived usefulness and attitude toward AI being the strongest predictors. Students with higher exposure to AI perceive it as more useful and develop positive attitudes toward its use, which directly affects their intention to adopt AI tools in accounting education. Ease of use and self-efficacy also enhanced positive attitudes, while technological anxiety and perceived risk were less influential.

These results suggest that educators, institutions, and technology developers should focus on providing AI exposure, user-friendly platforms, and skill-building opportunities to improve adoption among accounting students. This study fills a research gap in the Indian context, offering empirical evidence on AI acceptance in accounting education in West Bengal and providing insights for

curriculum design, training programs, and effective implementation of AI tools in higher education.

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