



International Journal of Artificial Intelligence and Machine Learning

Publisher's Home Page: <https://www.svedbergopen.com/>



Research Paper

Open Access

Impact of Artificial Intelligence on Management Accounting Practices and Strategic Decision-Making: Evidence From Indian Businesses

¹Mr. Samson, ²Dr. M Divya, ³Dr. R Anbuselvi, ⁴Dr. T. Joel Gnanapragash, ⁵Mr. K Selvakumar and ⁶Dr. P Brintha

¹Assistant Professor, Department of Commerce, Thiagarajar College, Madurai. E-mail: samson_commsf@tcarts.in

²Assistant Professor, Department of Commerce, Thiagarajar College, Madurai. E-mail: divya_commsf@tcarts.in

³Assistant Professor, Department of Commerce, Thiagarajar College, Madurai. E-mail: anbuselvi_commsf@tcarts.in

⁴Associate Professor, Department of Management, Thiagarajar College, Madurai. E-mail: joel_mba@tcarts.in

⁵Assistant Professor, Department of Commerce, Thiagarajar College, Madurai. E-mail: selvakumar_commsf@tcarts.in

⁶Assistant Professor, Department of Commerce, Thiagarajar College, Madurai. E-mail: brintha_commsf@tcarts.in

ABSTRACT

AI is fundamentally changing the role of management accounting from narrowly periodic, transaction-centered reporting to continuous analysis, forecasting and decision support. This paper examines the transformation experienced in India in organizations and decision making. In the absence of experiment or panel data at the firm level, this study relied on secondary data and evidence synthesis. The NASSCOM-EY AI Adoption index 2.0 survey (comprising 500 Indian firms representing seven sectors), the EY India C-suite GenAI evidence base, recent corporate disclosures from Indian firms, and peer-reviewed research on AI, machine learning and management accounting were the data sources underpinning evidence synthesis. The taxonomy maps AI to five categories: transaction and reporting automation, cost and profitability analysis, budgeting and forecasting, performance management, and strategic risk and decision support. AI will likely have the most impact on management accounting by compressing the information cycle by automating data preparation, enabling faster variance analysis, predictive forecasting, and anomaly detection and scenario modeling. AI will likely not replace management accountants in the near term. An analysis of Indian companies' maturity done with its 2024 AI maturity model found overall scores on a 4 point scale of 2.47 and that 87% were at the mid-zone 'Enthusiast' and 'Expert' levels. Data readiness, alignment with business processes, skills and governance could limit the implementation of proofs of concept. The paper proposes a human-AI management accounting framework and shows that strategic value results when analytical capability is combined with trustworthy data, explainability, professional judgement and governance. The findings show that AI can improve strategic agility and the business-partner role of management accountants in India, but measurable value requires organizational integration and not just technological adoption.

Keywords: Artificial intelligence; management accounting; strategic decision-making; predictive analytics; generative AI; India; finance transformation; management control.

1. Introduction

Management accounting has been used to translate data into information used for planning, control, performance evaluation and strategic choice. The traditional routine was based on periodic closing cycles, standard reports and variance analysis, with managerial interpretation. Digitalization has increasingly reshaped that architecture, with ERP, BI and RPA being augmented with ML, NLP, generative AI and increasingly agentic systems, so its implications cannot simply be reduced to faster bookkeeping or a spreadsheet with calculations. It can change the speed of information production, the range of information being analyzed, the capacity to predict and the way managers interact with financial and non-financial information.

Most applicable to firms in India, however, is India's AI Adoption Index 2.0, developed by NASSCOM and EY India. This index surveyed 500 firms in seven sectors that contributed the most to the Indian economy and calculated an overall maturity score of 2.47/4 in 2024 with a mixed impact of AI adoption across sectors. In addition, most of the firms in the survey fall into the intermediate categories, which suggests the central managerial challenge is no longer whether firms should experiment with AI or not, but how firms can integrate AI into their operating and decision-making processes as they move forward. Management accounting is also critical since budgeting, forecasting, cost control, pricing, working-capital management, investment appraisal and performance measurement all relate directly to choices regarding resource allocation.

The academic literature has evolved beyond pure big data and analytics as research topics to struggle with the ramifications of the emergence of the accountant role. More recent studies explore machine learning,

explainable, generative, or other forms of AI that automate repetitive tasks, generate predictions from large or complex datasets, and redefine professional boundaries. For example, in a systematic review of 91 articles, Abbas (2026) categorizes the changes that occur in accounting information, the composition of organizations and roles of accountants, and arising privacy, security, ethical and skills-related problems. Ranta, Ylinen and Järvenpää (2023) identify prediction, textual data, unstructured information and explainable AI as other areas of innovation in management accounting. Future research would need to consider the quality and governance, besides efficiency, of strategic decision-making.

1.1 Research Questions and Objectives

The investigation is guided by the following research questions:

- (RQ1) How is AI changing core management accounting practices in Indian businesses?
- (RQ2) Through what channels can AI-enabled management accounting improve strategic decision-making?
- (RQ3) What organizational, data, skill and governance constraints limit the realization of AI value?
- (RQ4) How is the role of the management accountant likely to change as AI becomes embedded in finance and operating processes?

Research Objectives

1. To examine the impact of Artificial Intelligence (AI) on management accounting practices in Indian businesses.
2. To analyse the role of AI in improving budgeting, forecasting, cost management, performance measurement, and management control.
3. To evaluate the contribution of AI-enabled management accounting to strategic decision-making, particularly in relation to resource allocation, risk assessment, and organizational performance.
4. To identify the major technological, organizational, data-related, skill, and governance challenges affecting the adoption and effective utilization of AI in management accounting.
5. To assess the changing role of management accountants in an AI-driven business environment and examine the importance of human judgement, professional expertise, and AI governance in strategic decision-making.

2. Review Of Literature

The relationship between digital technology and accounting predates the current AI cycle. Bhimani and Willcocks (2014) argued that digitisation and big data change the nature of accounting information by expanding data volume, velocity and variety. Vasarhelyi et al. (2015) similarly described big data as a challenge to established accounting models and an opportunity for new forms of analysis. Appelbaum et al. (2017) linked business analytics and enterprise systems to managerial accounting, highlighting the potential for more timely and analytically rich internal information.

The literature on management accountants' roles emphasizes that technology can simultaneously automate tasks and increase the need for interpretation. Andreassen (2020) describes digital technology as capable of producing both opportunities and tensions for management accountants. When routine extraction, reconciliation and reporting are automated, accountants can devote more attention to analysis and business partnering; however, this shift requires technical literacy, cross-functional collaboration and the ability to challenge algorithmic outputs rather than simply accept them.

Machine learning deepens this transformation because it moves beyond rules-based automation. Nielsen (2022) observes that management accounting research has historically made limited use of machine-learning techniques despite their relevance for classification, clustering, anomaly detection and prediction. Ranta et al. (2023) identify four especially promising areas: extracting value from textual data, converting qualitative information into measurable variables, improving estimates and predictions, and using explainable AI to interpret complex models. These applications are directly relevant to forecasting, customer and product profitability, cost-driver analysis, working-capital risk and performance diagnostics. Recent research has shifted from technical possibility to adoption conditions. Zhang et al. (2026), based on interviews with representatives of 41 companies, identify institutional and individual factors that shape managerial-accounting AI adoption. Their findings are important because AI implementation is not a purely technical optimization problem. User trust, perceived usefulness, organizational support, data availability and ethical concerns influence whether AI is adopted and how it is used. This is consistent with technology-organization-environment and technology-acceptance perspectives.

Ethics and accountability form a parallel stream. Lehner et al. (2022) examine ethical challenges in AI-based accounting and auditing decisions, while Zhang et al. (2023) analyse the ethical impact of AI in managerial accounting. The central concern is that algorithmic accuracy does not automatically establish managerial legitimacy. A forecast can be statistically strong yet unsuitable for a strategic decision if the underlying data are biased, the model is not explainable, or decision rights are unclear. For management accounting, which often supports decisions with distributive consequences—budgets, targets, product continuation, headcount, pricing and investment—human oversight remains essential.

Generative AI expands the interface between managers and accounting information. Instead of requiring users to navigate dashboards or write code, large language models can summarize variance drivers, draft management commentary, query enterprise data through natural language and generate scenarios. Abbas (2026) treats large language models as part of the emerging management-accounting research frontier. Atsalakis et al. (2026) further examine generative AI in managerial accounting and emphasize technical, institutional, ethical and cognitive implications. The relevant shift is from automation of structured transactions toward conversational access to organizational knowledge and analytical assistance. The literature nevertheless leaves an India-specific gap. Indian firms operate in a setting characterized by rapid digitalization, large differences in enterprise scale, significant sectoral heterogeneity and a growing data-protection and responsible-AI agenda. Generic global findings cannot simply be assumed to apply uniformly. Evidence is required on adoption maturity, use-case scaling, data readiness and the organizational conditions under which AI becomes part of finance and strategic decision routines.

2.1 Theoretical Foundation

The conceptual foundation integrates three complementary lenses. The first is the Technology-Organization-Environment (TOE) framework to describe adoption through technological, organizational and environmental factors. This study defines the technology dimension as data architecture, system integration and model capability; the organization dimension as leadership commitment, finance skills and governance; and the environment dimension as regulation, competition and sector norms.

The second is the resource-based and dynamic-capabilities view of the firm. According to this view, AI creates strategic value only when bundled with complementary resources such as proprietary data, process knowledge, skilled people and decision routines. That same AI model would therefore produce different outputs across organizations. The management accounting dynamic capability is no longer just reporting historical performance, it is sensing patterns, simulating alternatives, and reallocating resources accordingly.

The third is the socio-technical perspective. Management accounting is a system of people, routines, information and control, not merely a software layer. AI can alter authority and information asymmetry by changing who can access analysis, how quickly exceptions are detected and how recommendations are produced. Strategic value consequently depends on the joint design of technology and human judgement.

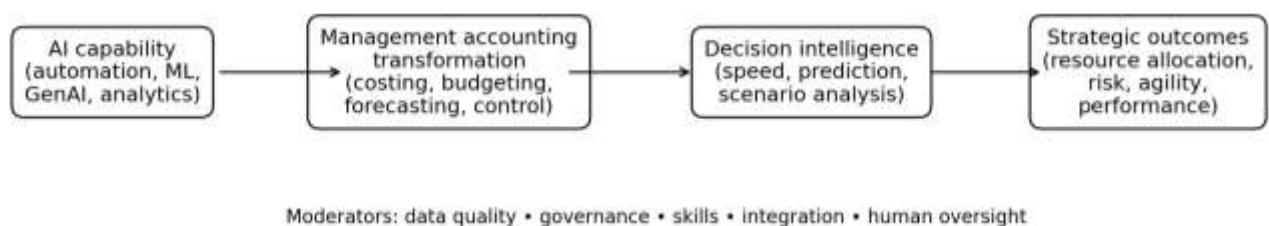


Figure 1. Human-AI management accounting transmission framework.

Source: Authors' conceptualization based on the literature reviewed in this study.

3. INDIAN ENTERPRISE AI CONTEXT

The Indian enterprise context shows both strong momentum and incomplete institutionalization. NASSCOM's AI Adoption Index 2.0 surveyed 500 organizations across banking and financial services, consumer packaged goods and retail, manufacturing, healthcare and pharmaceuticals, energy and utilities, telecommunications/media/entertainment, and transport and logistics. The 2024 aggregate score of 2.47 on a four-point maturity scale was only modestly above the 2022 score of 2.45, even though the later survey covered a broader sector base and placed greater emphasis on execution, production use cases and organizational readiness.

The distribution is more informative than the aggregate. Approximately 12% of surveyed enterprises were at the Explorer stage, 42% at Enthusiast, 45% at Expert and about 1% at Evangelist. Thus, 87% occupied the two middle stages. This pattern indicates that Indian firms are not generally unfamiliar with AI; rather, many face the harder problem of scaling from experimentation to repeatable enterprise use. The report identifies alignment with business goals, standardized and compliant data, dedicated budgets, skills and proof-of-concept-to-production speed as key constraints.

Data readiness is especially relevant for management accounting. EY's Data 4.0 discussion of the NASSCOM-EY evidence notes that more than 60% of organizations in several major sectors had standardized data at enterprise or business-unit level, while 32% still lacked an AI-ready data backend. Management accounting models depend on consistent definitions of products, customers, cost centres, transactions and performance indicators. If master data are fragmented or inconsistent, AI may accelerate analysis without improving its reliability.

EY India's 2025 Aldea of India report adds a generative-AI perspective. Its survey of more than 125 Indian C-suite executives found that many enterprises were investing or experimenting, while production deployment and cost measurement remained substantially less mature. This distinction is important for management accounting because finance leaders ultimately have to evaluate return on AI investment, allocate costs, compare use cases and decide whether pilots deserve scaled funding.

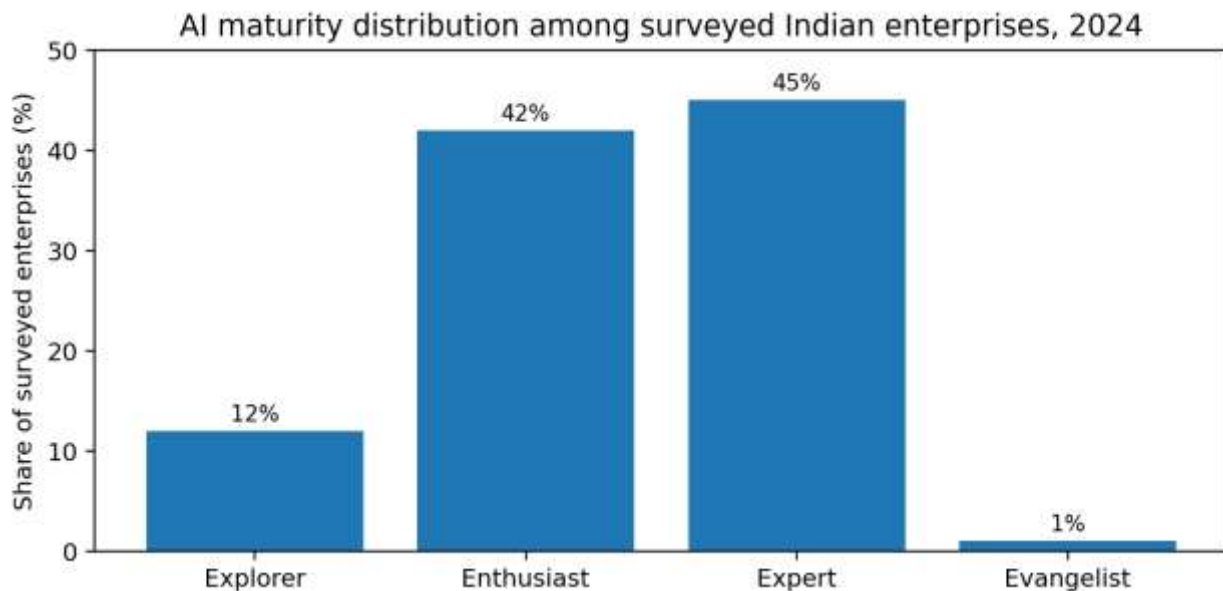


Figure 2. AI maturity distribution among surveyed Indian enterprises, 2024.

Source: NASSCOM, AI Adoption Index 2.0 (2024). Percentages are rounded as reported.

Table 1. India-specific evidence used in the study

Evidence source	Coverage	Key indicator	Relevance to management accounting
NASSCOM AI Adoption Index 2.0 (2024)	500 Indian companies; seven sectors	Aggregate maturity 2.47/4; 87% in Enthusiast/Expert stages	Shows scale, maturity and constraints on AI execution
EY India, Aldea of India (2025)	125+ Indian C-suite executives	Investment/experimentation exceeds production deployment; limited cost attribution	Links AI strategy, ROI, cost measurement and scaling decisions
EY Data 4.0 (2024)	Indian enterprise data-readiness evidence	32% reported as lacking an AI-ready data backend	Data quality conditions forecasting, costing and analytics
Infosys Integrated Annual Report 2024-25	Large Indian IT services enterprise	AI-first strategy; 400+ GenAI projects delivered; 270,000 AI-aware employees	Illustrates scaling, skills and AI-enabled process transformation
ICICI Bank Annual Report 2024-25	Large Indian private-sector bank	AI use cases across functions including decision support and credit risk	Shows AI embedded in risk and operating decisions
Poonawalla Fincorp Annual Report 2024-25	Indian NBFC	AI/ML decisioning, early-warning and fraud tools; AI-led credit automation	Illustrates analytics in credit judgement, risk and control

4. Methodology

A descriptive-analytical secondary-data design is adopted. This choice is deliberate. To make a claim based on original data from Indian companies would require a survey, an interview schedule or a firm-level dataset that I cannot ethically imagine. This alternative design makes use of verifiable enterprise surveys,

corporate disclosures and peer-reviewed research to analyze patterns and mechanisms without making any causal claims.

Three source layers were collected. The first is India-wide enterprise evidence, of which the NASSCOM-EY AI Adoption Index 2.0 and EY India GenAI Research make up the majority. The second layer consists of corporate disclosures that report their examples of actualized use of AI in their business contexts in tech services and financial services in India. The third layer is peer-reviewed accounting and information-systems literature used to interpret their mechanisms, adoption conditions and governance risks.

The analysis is conducted stepwise: First, the reported AI use cases are assigned to one of the five management accounting functions process/reporting automation, costing and profitability, budgeting/forecasting, performance management, and risk/strategic decision support. The second step links function types such as forecast, prediction, anomaly detection, scenario analysis or information demand to decision types. The last step assesses readiness levels on implementation moderators such as data readiness, integration, skills, governance and human involvement. Fourth, enterprise surveys, corporate cases and academic research are triangulated to separate universal regularities from source-specific claims as above.

Inferential statistics are not provided because the surveys have different sample and construct populations, and pooled estimation is not possible with firm-level microdata that are not publicly available. The listed percentages are descriptive indicators from their original data sources. This avoids pseudo-precision, in that it keeps a distinction between the indicators of its adoption and its actual effects on profitability or decision-making.

4.1 Analytical Propositions

- **P1:** AI adoption is associated with a shift in management accounting from periodic reporting toward continuous and predictive analysis.
- **P2:** The strategic effect of AI is mediated by management-accounting integration; automation alone is insufficient to improve strategic decisions.
- **P3:** Data quality, system integration, skills and governance positively condition the conversion of AI capability into decision value.
- **P4:** AI changes the management accountant's role from data preparation toward interpretation, challenge, business partnering and governance.

5. Results And Analysis

5.1 Automation and the Compression of the Reporting Cycle

The first observable effect of AI is the compression of the accounting information cycle. Traditional management reports are created by extracting, reconciling, classifying, spreadsheet manipulation, and commentary writing. Robotic Process Automation and artificial intelligence can partially automate these processes. Generative systems can help with narrative explanation and exception summary preparation. Latency of the decision matters: a variance report a month old is different from a decision based on near real-time operating signals. Indian corporations bear testimony to the shift. Infosys's AI first enterprise strategy, its hundreds of generative-AI projects, and its mention of BPM operations in finance or accounting with explicit AI focus suggest that automation is not a monolith. The goal is to decouple process work from judgment work. Management accountants can focus on why a variance occurred, whether it is persistent, and what response is economically justified. They remain on the hook for judgment, but machines automate process work.

Another impact of automation on the design of controls is that continuous anomaly detection can detect unusual transactions, cost deviations or process exceptions sooner than periodic human checks. Automated exception generation can produce false positives and additional alert fatigue, making it important for management accounting to set materiality thresholds, escalation rules and monitor model performance, similar to tolerances and responsibility centres in traditional control systems.

5.2 Cost Management, Profitability and Resource Allocation

AI could support more granular cost management, being better able to understand nonlinear relations between volume, product mix, process duration, energy consumption, logistical requirements, customer behavior, and the intensity of service needed than traditional allocation models. In principle, this enables businesses to transition from fixed cost pools to flexible estimates of cost-to-serve to inform customer profitability, channel strategy, make-or-buy decisions and process design. Interpretability can only be relied on in certain circumstances. A model could simply predict that a customer segment is a costly one to serve without explaining why. Management accountants need to be able to identify controllable cost drivers of the model output, and be able to explain the reasoning behind the allocation logic. Explainability makes most sense where costs from an AI system affect pricing, customer prioritization, or investment decisions.

5.3 Budgeting, Forecasting and Scenario Planning

Forecasting is one of the clearest bridges between AI and strategy. Traditional budgets are based on extrapolations, manager assumptions, and periodic reassessments. As processes become data-driven, machine learning can deal with big data and new data. It continually updates their forecasts of sales, cash flows, demand, working capital, and capacity. Generative AI complements quantitative models by providing qualitative narratives, extracting signals from text, and enabling managers to think in scenarios. For management accounting, this means shifting the focus from producing one budget number to managing a distribution of likely outcomes. When making planning decisions involving capacity, inventory, hires, price, or capital investment, a comparison of scenarios, or consideration of uncertainty, is often useful. The accountant's role is to challenge the model by questioning the assumptions, checking that relationships stay the same, testing the sensitivity to bad outcomes, and translating probabilities into business intent.

5.4 Performance Measurement and Management Control

AI broadens the types of performance measures from post financial lag indicators to text analytics, process data, customer interactions, operational sensor data, and workforce data that can be linked to the financial outcomes and provide capabilities for earlier indicators of margin pressure, service deterioration or execution risk. Instrumented in balanced-scorecard terms, AI can strengthen the causal relationship between operational drivers and financial outcomes, while measurement itself via algorithm can provide even more control. If algorithmic performance measurement is done on a non-transparent model, then fairness of a measure decreases even as the measurement level increases. One of the governance roles of management accountants is to decide what is useful, what weight is given, and what is understood and can be challenged by employees, to be the basis on which they are evaluated. Literature on ethics of AI in accounting is relevant.

5.5 Risk Analytics and Strategic Decision Support

Financial services are highly visible for Indian use cases, as data is generated from credit, financial fraud, liquidity, and customer behavior. ICICI Bank's 2024-25 annual report shows use cases for AI across business functions to improve operational efficiency and decision making, including traditional AI use in credit risk management. Poonawalla Fincorp cites AI/ML credit decisioning, behavioral scorecards, early warning signals and fraud tools as examples of AI driving the intersection of measurement, risk management and strategy. Risk analytics expands the definition of decision support in management accounting. Assessment of strategic profitability would not be possible without looking at risk. Use of AI to model expected loss, its emergence or portfolio effects can allow finance teams to focus beyond just revenue to also consider risk-adjusted returns, particularly in capital allocation and growth decisions in financial services.

6. EVIDENCE SYNTHESIS: HOW AI CHANGES MANAGEMENT ACCOUNTING

Table 2. AI-enabled changes in management accounting and strategic implications

Management accounting domain	AI-enabled practice	Immediate effect	Strategic decision use	Principal risk
Reporting & close	Automated classification, reconciliation, narrative summaries	Faster cycle; fewer manual steps	Earlier intervention and exception management	Automation error; weak audit trail
Cost & profitability	Driver detection, cost-to-serve prediction, anomaly analysis	Greater granularity	Pricing, customer/channel strategy, process redesign	Opaque allocation logic
Budgeting & forecasting	ML forecasts, rolling updates, scenario generation	Forward-looking information	Capacity, inventory, hiring, cash and capital planning	Model drift; structural breaks
Performance management	Linking financial and non-financial signals	Earlier indicators	Strategic control and resource reallocation	Metric overload; unfair evaluation
Risk & control	Fraud detection, early-warning systems, risk scoring	Faster risk identification	Risk-adjusted growth and capital allocation	Bias, false positives, accountability

Decision interface	Natural-language querying and GenAI summaries	Wider analytical access	Faster cross-functional decisions	Hallucination, confidentiality, over-reliance
--------------------	---	-------------------------	-----------------------------------	---

8. MANAGERIAL AND POLICY RECOMMENDATIONS

- Build AI use cases around decision problems, not around technology availability. Start with a well-defined management-accounting decision and a measurable baseline for that decision.
- Create an AI-ready finance data layer for every source, standardizing master data, documenting definitions, controlling access, and tracking transformations.
- Model performance reviews should be rolling. Forecast accuracy, false-positive rates, bias indicators, and model drift should be tracked as carefully as any other management-control measure.
- Human accountability: AI may make suggestions or act within a certain range, but strategic decisions of material importance remain as a result of human choices.
- Explainability should be weighted proportionately to the seriousness of the decision, with more documentation and challenge at stake.
- Measuring total economics, including implementation costs, data preparation, cloud or compute costs, licensing and integration costs, as well as controls, training and operationalization costs (not just the software/application).
- Develop management accountants' competency in analytics, prompt/model interrogation, scenario design, data governance and strategic communications.
- Use post-implementation reviews to compare the promised benefits against those realized, and stop or redesign those where decision value cannot be measured.

9. LIMITATIONS AND FUTURE RESEARCH

However, there are four main limitations. First, the paper is based on secondary evidence and does not measure the causal impact of AI adoption on firm performance or strategic decision-making. Second, enterprise surveys tend to focus on large firms, where more advanced uses of digital technology are common and where adopting such technology holds different risks and challenges than for SMEs. Third, corporate annual reports are good for use case identification, but not unbiased measures of technology performance. Fourth, rapid technological change means that the boundary between automation, machine learning, generative AI and agentic AI is moving faster than traditional research cycles.

Future studies should establish firm-level, or business-unit, panel datasets between AI maturity and management-accounting outcomes such as forecasting error, budgeting-cycle time, close-cycle time, inventory days, working-capital performance, cost deviation, decision lead time, and risk-adjusted profitability. Future studies must measure adoption in terms of production intensity and functional integration rather than at the level of yes/no.

Primary research could involve a stratified survey of CFOs, controllers, management accountants and business-unit managers in India to provide empirical evidence of the relationships proposed and their testing using structural equation modeling. These constructs might include AI capability, data quality, finance-business integration, explainability, user trust, governance maturity, decision speed, and perceived decision quality. Interviews could then clarify why such technologies have disparate effects across sectors. A relevant question concerns human-AI complementarity. Future studies should compare human decisions made independently, decisions made in co-operation with an AI, and decisions made using highly automated processes under conditions of varying uncertainty and strategic ambiguity. This would shift the literature from perceptions of adoption to evidence of the decision.

10. Conclusion

Artificial Intelligence is disrupting management accounting through shorter reporting cycles, deeper analytical capabilities, more accurate forecasting and more democratized decision support information. Evidence from India suggests very high levels of early stage adoption, but also a divide between experimentation and wide-scale deployment in organizations. Most of the NASSCOM-EY survey sample was in intermediate maturity, and EY's GenAI work identified additional issues in scaling production, measuring ROI, and cost attribution, so the strategic implications are conditional at best. AI can improve the timeliness and scope of decision-making information for pricing, forecasting, risk and resource allocation and performance management. Yet, decision-making may not improve. The quality and integration of data, the required skills to use the technology, explainability of AI and governance determine whether the outputs serve as managerial knowledge.

References

1. Abbas, K. (2026). Management accounting and artificial intelligence: A comprehensive literature review and recommendations for future research. *The British Accounting Review*, 58(2), 101551. <https://doi.org/10.1016/j.bar.2025.101551>
2. Andreassen, R.-I. (2020). Digital technology and changing roles: A management accountant's dream or nightmare? *Journal of Management Control*, 31, 209–238. <https://doi.org/10.1007/s00187-020-00303-2>
3. Appelbaum, D., Kogan, A., Vasarhelyi, M., & Yan, Z. (2017). Impact of business analytics and enterprise systems on managerial accounting. *International Journal of Accounting Information Systems*, 25, 29–44.
4. Atsalakis, G. S., Atsalaki, I., Lemonakis, C., et al. (2026). Generative artificial intelligence and managerial accounting. *Information Systems Frontiers*. <https://doi.org/10.1007/s10796-026-10763-x>
5. Bhimani, A., & Willcocks, L. (2014). Digitisation, 'big data' and the transformation of accounting information. *Accounting and Business Research*, 44(4), 469–490.
6. EY India. (2024). Data 4.0: Making your data AI-ready. EY.
7. EY India. (2025). The Aldea of India 2025: How much productivity can GenAI unlock in India? EY.
8. ICICI Bank. (2025). Annual Report 2024–25. ICICI Bank Limited.
9. Infosys Limited. (2025). Integrated Annual Report 2024–25. Infosys Limited.
10. Lehner, O. M., Ittonen, K., Silvola, H., Ström, E., & Wührleitner, A. (2022). Artificial intelligence based decision-making in accounting and auditing: Ethical challenges and normative thinking. *Accounting, Auditing & Accountability Journal*, 35(9), 109–135.
11. NASSCOM. (2024). AI Adoption Index 2.0: Tracking India's Sectoral Progress in AI Adoption. NASSCOM, with knowledge support from EY India.
12. Nielsen, S. (2022). Management accounting and the concepts of exploratory data analysis and unsupervised machine learning: A literature study and future directions. *Journal of Accounting & Organizational Change*, 18(5), 811–853. <https://doi.org/10.1108/JAOC-08-2020-0107>
13. Pavlovic, M., Gligoric, C., Zdravkovic, F., & Pavlovic, D. (2024). Revolutionizing management accounting: The role of artificial intelligence in predictive analytics, automated reporting, and decision-making. *Business & Management Compass*, 68(4), 23–42. <https://doi.org/10.56065/nxn2gx53>
14. Poonawalla Fincorp Limited. (2025). Annual Report 2024–25. Poonawalla Fincorp Limited.
15. Ranta, M., Ylinen, M., & Järvenpää, M. (2023). Machine learning in management accounting research: Literature review and pathways for the future. *European Accounting Review*, 32(3), 607–636. <https://doi.org/10.1080/09638180.2022.2137221>
16. Sutton, S. G., Holt, M., & Arnold, V. (2016). The reports of my death are greatly exaggerated—Artificial intelligence research in accounting. *International Journal of Accounting Information Systems*, 22, 60–73.
17. Vasarhelyi, M. A., Kogan, A., & Tuttle, B. M. (2015). Big data in accounting: An overview. *Accounting Horizons*, 29(2), 381–396.
18. Vărzaru, A. A. (2022). Assessing artificial intelligence technology acceptance in managerial accounting. *Electronics*, 11(14), 2256.
19. Zhang, C., Zhu, W., Dai, J., Wu, Y., & Chen, X. (2023). Ethical impact of artificial intelligence in managerial accounting. *International Journal of Accounting Information Systems*, 49, 100619.
20. Zhang, C., Zhu, W., Dai, J., Wu, Y., & Chen, X. (2026). Drivers and concerns of adopting Artificial Intelligence in managerial accounting. *Accounting & Finance*, 66(2), 1939–1971. <https://doi.org/10.1111/acfi.13404>