Article history:
Received 10 June 2025
Revised 24 September 2025
Accepted 01 October 2025
Published online 20 October 2025

Journal of Resource Management and Decision Engineering

Volume 4, Issue 4, pp 1-11

Futures Studies on Artificial Intelligence in Management Accounting

Mohsen. Aboeuimehrizi[1], Mahmoud. Moeinadin[1*], Akram. Taftiyan [1], Mohammad. Sadeghi Sarcheshmeh [2]

[1] Department of Accounting, Ya. C., Islamic Azad University, Yazd, Iran
[2] Department of Electrical, Ya. C., Islamic Azad University, Yazd, Iran

*** Corresponding author email address**: Mahmoudmoein1352@iau.ac.ir

Article Info

Article type:
Original Research

How to cite this article:
Aboeuimehrizi, M., Moeinadin, M., Taftiyan, A., & Sadeghi Sarcheshmeh, M. (2025). Futures Studies on Artificial Intelligence in Management Accounting. *Journal of Resource Management and Decision Engineering, 4*(4), 1-11.
https://doi.org/10.61838/kman.jrmde.168

ABSTRACT

The present study was conducted with the aim of exploring the future applications of artificial intelligence (AI) in management accounting and is applied and descriptive (non-experimental) in nature. Data collection was carried out using a mixed-methods approach, combining field and library research techniques. The tools employed included expert panels, semi-structured interviews, open-ended questionnaires, the fuzzy Delphi method, observation, and document analysis. The statistical population consisted of professors, doctoral students, members of the Management Accountants Association, and professional specialists in this field in Iran. Sampling was performed using theoretical and snowball methods, and interviews continued until theoretical saturation was reached. Data analysis was conducted both qualitatively and quantitatively, leading to the identification of key drivers in management accounting education and research. Based on the results of the fuzzy Delphi analysis, the technology of deep learning ranked first with a fuzzy mean of 3.7 and was recognized as the most critical driver. Subsequently, natural language processing (NLP) with a mean of 3.4 was also identified among the accepted technologies. Blockchain technology, with a score of 3.1, was evaluated as conditional and requires further investigation. Additionally, explainable artificial intelligence (XAI) was proposed as an emerging driver that could play a significant role in enhancing transparency, trust, and regulatory compliance. The findings of this research indicate that the future of management accounting will be directly influenced by technological advancements in AI. To leverage these technologies effectively, strategic planning and investments in education and infrastructure development are essential.

Keywords: *Futures studies on artificial intelligence, management accounting, deep learning, natural language processing, blockchain*

1. Introduction

Artificial intelligence (AI) has rapidly evolved from a set of experimental techniques to a pervasive general-purpose technology reshaping organizational information processing, decision-making, and control systems, with profound implications for management accounting (MA) as the nerve center of planning, budgeting, performance measurement, and strategic steering (Barreto et al., 2025; Kerr et al., 2025). In contemporary enterprises, MA is increasingly expected to translate data exhaust from interconnected digital operations—enterprise systems, platforms, sensors, and customer interfaces—into actionable insights that enhance value creation and risk governance. The confluence of AI, big data analytics, and distributed technologies is therefore not a peripheral modernization but a structural shift in the epistemic foundations, routines, and competencies of MA, necessitating new architectures of information quality, assurance, explainability, and ethical oversight (Lehner et al., 2022; Marcus et al., 2025; Zhang et al., 2023).

The literature documents a broadening scope for AI-enabled MA spanning predictive cost behavior, dynamic budgeting, anomaly detection, demand forecasting, and scenario planning, with algorithmic advances allowing models to learn complex dependencies and temporal patterns in high-dimensional data streams (Abbas, 2025; Sharma et al., 2024). Beyond efficiency, the strategic promise lies in augmenting managerial cognition—surfacing weak signals, quantifying uncertainty, and enabling continuous, closed-loop control aligned with organizational strategy. At the same time, researchers highlight an implementation gap shaped by data governance maturity, skill readiness, and socio-technical fit within accounting routines, indicating that the diffusion of AI in MA is as much about institutionalization and capability-building as it is about algorithms (Barreto et al., 2025; Kroon et al., 2021).

Technologically, the current wave of adoption is catalyzed by advances in machine learning (ML), especially deep learning architectures that extract hierarchical features from structured and unstructured sources, and by generative AI that can synthesize, summarize, and simulate domain representations to assist judgment under uncertainty (D'Angelo & Palmieri, 2021; He et al., 2025). Deep neural networks—convolutional, recurrent, and hybrid autoencoders—have demonstrated superior capacity for spatiotemporal feature extraction in streams and logs, a capability transferable to transaction flows and operational telemetry that underpin MA dashboards and early warning systems (D'Angelo & Palmieri, 2021; Machado & Karray, 2022). The availability of foundation models and model-as-a-service platforms further lowers entry barriers, enabling controllership and FP&A teams to experiment with AI services within governed environments (Marcus et al., 2025; Maslej et al., 2024).

At the macro level, digital transformation has altered the cost of information, expanded the feasible frontier of control system design, and reconfigured the role identity of accountants from scorekeepers to analytics translators and strategic business partners (Gonçalves et al., 2022; Hossein et al., 2024). Systematic reviews emphasize that curricula and professional training must pivot toward data engineering literacy, model governance, and cross-functional communication, while organizations should rethink the design of MA processes to exploit continuous, data-driven feedback loops rather than static period-based reporting (Barreto et al., 2025; Berikol & Killi, 2021). The shift is not only technical but normative: as AI participates in decisions affecting resource allocation and performance evaluation, questions of fairness, transparency, and accountability move to the center of MA research agendas (Lehner et al., 2022; Zhang et al., 2023).

Empirical and conceptual studies concur that AI adoption in MA is conditioned by organizational context—governance structures, risk appetite, regulatory exposure, and public accountability—leading to heterogeneous trajectories across sectors (Alwell et al., 2024; Sharma et al., 2024). In public finance and government agencies, the promise of AI as a budgeting tool has attracted interest for enhancing forecasting accuracy, prioritization, and participatory transparency, yet also surfaces unique requirements for auditability, explainability, and stakeholder legitimacy (Alwell et al., 2024; Lee et al., 2024). Private-sector deployments often prioritize predictive analytics for revenue and cost drivers, cash flow risk, and working capital optimization, with integration into rolling forecasts and driver-based models (Abbas, 2025; Sharma et al., 2024). Across both domains, the MA function acts as a hub connecting operational data, planning processes, and governance forums where AI outputs must be interpretable and decision-useful (Kerr et al., 2025; Secinaro et al., 2024).

A complementary stream examines blockchain's potential to restructure assurance and trust mechanisms in accounting information flows by enabling tamper-evident records, programmable controls, and shared data provenance across organizational boundaries (Abad-Segura et al., 2021; Secinaro et al., 2021). In MA contexts, blockchain-enhanced supply chain visibility and real-time verification could reduce reconciliation costs, tighten variance analyses, and support sustainability reporting through secure data lineage (Al-Zaqeba et al., 2022; Mahdani et al., 2023). Yet adoption is tempered by scalability constraints, integration costs, and governance complexity, suggesting that benefits are contingent on network coordination and fit with existing control architectures (Al Yasin & Pourzamani, 2022; Noori Doabi et al., 2023). Managers thus face a portfolio of digital options—AI for inference and prediction, blockchain for data integrity and shared controls—whose complementarities require careful architectural design in MA systems (Abad-Segura et al., 2021; Yan et al., 2023).

The infusion of AI also reframes classic MA instruments. Budgeting evolves from annual baselines to adaptive, driver-based, and scenario-rich processes powered by predictive and generative models, enabling rolling forecasts and sensitivity analyses at higher cadence (Kerr et al., 2025; Lee et al., 2024). Costing and profitability analyses leverage granular behavioral models of cost drivers, price elasticity, and customer lifetime value; inventory policies incorporate AI for demand sensing, reorder optimization, and anomaly detection (Sharma et al., 2024; Singh & Adhikari, 2023). Risk management gains from early warning signals drawn from multivariate patterns across operations and the external environment, while capital allocation can be stress-tested under simulated macro- and micro-scenarios generated by foundation models (Marcus et al., 2025; Maslej et al., 2024). Such redesign shifts the emphasis from ex post variance explanations to ex ante guidance and continuous steering (Barreto et al., 2025; Gonçalves et al., 2022).

Despite these promises, the literature cautions against technological determinism. Outcomes are mediated by data quality, process discipline, and the socio-cognitive dynamics of decision-makers who must interpret model outputs under time pressure and uncertainty (Kroon et al., 2021; Secinaro et al., 2024). Ethical concerns—bias, opacity, and the distribution of accountability—are acute where AI influences performance evaluation and incentive contracts (Lehner et al., 2022; Zhang et al., 2023). Studies call for robust model risk management, including validation, monitoring for concept drift, and counterfactual explanations that align with the informational needs of boards, auditors, and regulators (Lehner et al., 2022; Zhang et al., 2023). This is especially salient in domains like credit risk assessment and fraud detection, where false positives/negatives carry material financial and reputational consequences (Abbas, 2025; Machado & Karray, 2022).

International comparisons add nuance by showing that national scientific advantages and institutional infrastructures shape the pace and pattern of adoption. Bibliometric and informetrics analyses reveal differentiated capabilities across countries in producing and absorbing AI- and blockchain-related knowledge in accounting and finance, with implications for policy and talent strategies (Abramo et al., 2022; Mediaty et al., 2024). Sectoral studies similarly highlight that eco-efficiency and sustainability agendas can be amplified when MA integrates big data analytics and environmental cost tracking, but only when digital environmental management accounting practices are embedded to bridge data to sustainability KPIs (Abdelhalim, 2023; Abdelhalim et al., 2023). In manufacturing and logistics, supply chains benefit from blockchain-enabled transparency and AI-driven optimization, provided that inter-firm governance supports data sharing and standardization (Al-Zaqeba et al., 2022; Yan et al., 2023).

At the organizational layer, adoption determinants include leadership orientation, digital readiness, and the microfoundations of skill and role identity among MA professionals. Evidence indicates that AI reconfigures required competencies toward analytics literacy, data storytelling, and the stewardship of model governance artifacts (data dictionaries, model cards, and control narratives) (Hossein et al., 2024; Kroon et al., 2021). Change programs that combine upskilling with process redesign and technology orchestration—rather than pursuing tool-centric deployments—report more sustainable benefits (Berikol & Killi, 2021; Gonçalves et al., 2022). Public-sector findings further suggest that uncertainty about accountability and procurement constraints can impede diffusion, even when perceived usefulness for budgeting and service performance is high (Alwell et al., 2024; Lee et al., 2024).

From a systems perspective, the integration of AI into management information systems (MIS) provides a backbone for MA analytics services—data ingestion, feature stores, model pipelines, and monitoring—which, when well designed, can reduce decision latency and improve process conformance (Hidayat et al., 2024; Susilo & Susanto, 2024). Conceptual models such as the AIMA framework propose role-mapping between management accountants and AI agents, delineating tasks for automation, augmentation, and oversight to optimize human–machine teaming in planning and control cycles (Panigrahi, 2024; Sharma et al., 2024). Exploratory case studies likewise show that the effectiveness of AI-in-MA hinges on aligning analytics use cases to salient decision problems, refining data semantics for cost objects and drivers, and instituting feedback loops that learn from decision outcomes (Barreto et al., 2025; Secinaro et al., 2024).

The research frontier also examines domain-specific applications. In credit-intensive settings, hybrid ML ensembles can improve risk stratification of commercial customers, thereby informing pricing, limits, and provisioning—downstream MA artifacts that shape profitability steering and risk-adjusted performance measures (Kerr et al., 2025; Machado & Karray, 2022). In inventory and operations, AI supports demand sensing and adaptive policies that cut holding and stockout costs, with MA translating these operational gains into financial KPIs and rolling forecasts (Sharma et al., 2024; Singh & Adhikari, 2023). For sustainability-oriented MA, embedding environmental drivers and blockchain-verified data into cost and performance models strengthens credibility and decision relevance of ESG-related budgeting and variance analysis (Abad-Segura et al., 2021; Abdelhalim et al., 2023).

Blockchain's institutional implications for MA are both enabling and disruptive. By substituting or complementing intermediary-based trust with cryptographic assurance and consensus, blockchains can transform trust accounting and inter-organizational control, albeit with nuanced trade-offs between decentralization, performance, and governance (Al Yasin & Pourzamani, 2022; Secinaro et al., 2021). Studies note that while blockchain may reduce audit friction and enhance traceability, benefits depend on network design, smart contract robustness, and alignment with regulatory frameworks—variables that MA must incorporate into risk assessments and cost–benefit analyses (Mahdani et al., 2023; Noori Doabi et al., 2023). Early evidence from financial managers suggests perceived improvements in reporting timeliness and reliability, but realization requires integration with legacy systems and careful migration strategies (Pourabi et al., 2024; Rabiei et al., 2024).

Ethical, legal, and governance considerations remain core to responsible AI in MA. Scholars advocate normative frameworks that align algorithmic decision-making with professional values, articulating duties of care, transparency, and contestability for models influencing budgets, performance evaluation, and resource allocation (Lehner et al., 2022; Zhang et al., 2023). Explainability and auditability are not generic desiderata; in MA they must map to concrete justifications for variances, assumptions in driver-based models, and the traceability of adjustments—requirements that guide model selection (e.g., interpretable models for high-stakes uses) and the design of controls over AI life cycles (Kerr et al., 2025; Zhang et al., 2023). Governance patterns that combine policy, process, and tooling—model inventories, access controls, drift monitoring—are increasingly seen as prerequisites for scaling AI beyond isolated pilots (Maslej et al., 2024; Secinaro et al., 2024).

Against this backdrop, national and sectoral research streams underscore the need for context-sensitive roadmaps. Reviews focused on MA and AI synthesize fragmented evidence into agendas calling for longitudinal evaluations of performance impacts, cross-functional collaboration models, and comparative studies across regulatory environments (Abbas, 2025; Barreto et al., 2025). Regional analyses also point to opportunities for latecomers to leapfrog by aligning scientific capability development with priority use cases in budgeting, cost management, and supply chain analytics, supported by targeted policies for digital skills and data infrastructure (Abramo et al., 2022; Mediaty et al., 2024). Thought leadership from practice complements this by highlighting lessons from pilots—start with tractable, high-signal problems; invest in data semantics; and embed change management to build trust in model-assisted decisions (Berikol & Killi, 2021; Gonçalves et al., 2022).

This study contributes to the evolving conversation by foregrounding the future drivers of AI in MA and by situating their adoption within a socio-technical and governance-aware lens. Building on prior work that identifies the transformative but uneven effects of AI and blockchain on accounting and auditing, the study emphasizes prioritization among candidate technologies (e.g., deep learning, NLP, blockchain, explainable AI) and articulates criteria for managerial selection grounded in decision-critical characteristics such as explainability, data lineage, and integration complexity (Abad-Segura et al., 2021; Kerr et al., 2025; Secinaro et al., 2021). The exploration aligns with evidence that organizational and individual factors co-determine adoption trajectories, necessitating strategies that combine capability development with robust governance and ethical safeguards (Alwell et al., 2024; Lehner et al., 2022). By integrating insights from AI index tracking, sectoral case studies, and normative scholarship, the study positions MA not merely as a beneficiary of AI but as a co-designer of responsible digital control systems that enhance decision quality and organizational resilience. The present study was conducted with the aim of exploring the future applications of artificial intelligence (AI) in management accounting

2. Methods and Materials

This study is classified as applied research in terms of its purpose and was conducted in a real-world context without the researcher's intervention; therefore, it is considered descriptive (non-experimental). Additionally, given the type of data used, this research adopts a mixed-methods design, employing both field and library research for data collection. Various techniques were applied to collect data, including expert panels, open-ended questionnaires, interviews, and the fuzzy Delphi method. Furthermore, the researcher also utilized observation, document analysis, and active participation where necessary.

The statistical population consisted of professors and doctoral students in management accounting, members of the Management Accountants Association, and professional management accounting specialists in Iran. In qualitative research, random sampling is usually inappropriate as it does not facilitate the identification of individuals with deep knowledge. Therefore, this study employed theoretical and snowball sampling. The expert sampling process was carried out using a judgmental and snowball approach, and interviews continued until theoretical saturation was achieved. Experts were selected based on their specialization, experience, and knowledge related to management accounting at the national level.

Expert panel sessions were organized in small groups of 2 to 5 members, with a total of 11 participants. Additionally, to gather insights from experts who could not attend physically, open-ended questionnaires were sent electronically, and 9 responses were received. Subsequently, semi-structured interviews were conducted with 12 national experts, either in person or via telephone. At the beginning of each interview, the researcher introduced themselves, explained the research objectives, and emphasized confidentiality. Participants were asked to recommend other individuals with relevant expertise if possible. Sampling continued until theoretical saturation was reached.

The semi-structured interviews, as the primary data collection tool, were designed with an exploratory approach. Questions were carefully formulated so as not to be overly broad, which could hinder the discovery of new topics, nor too narrow, which could limit discussion and exploration. The collected data were recorded through audio recording and note-taking, then categorized and analyzed.

After identifying the key drivers in the field of management accounting education and research, an initial version of the questionnaire was prepared based on the fuzzy Delphi method. This preliminary questionnaire underwent incremental validity review and revision by expert professors. Finally, the validated questionnaire, structured on a 5-point Likert scale (from “strongly agree” to “strongly disagree”), was distributed to experts in both online and Word file formats, and a total of 23 completed questionnaires were collected.

After identifying the initial list of drivers, these items were reviewed, refined, and adjusted based on the feedback of professors and experts. Ultimately, five key drivers in the field of information science and technology were selected, and the Delphi questionnaire was designed and distributed to experts based on these drivers. At this stage, 12 valid and usable questionnaires were received. It should be noted that the questionnaire underwent several rounds of expert review and revision; their feedback was integrated into the Delphi process to ensure its validity and reliability.

All participants held a PhD degree and were university faculty members whose academic backgrounds were primarily in accounting, management accounting, and information technology. Due to their specialized work in management accounting and advanced academic training, they possessed high levels of theoretical and practical knowledge. Additionally, all participants had considerable professional experience in areas such as management accounting, auditing, and financial management.

The Cronbach’s alpha test for the technology dimension, based on the responses of 12 Delphi experts, yielded a value of 0.33. The binomial test indicated that the number of favorable and unfavorable responses to each driver was not equal at a significance level of 0.09, with the imbalance favoring positive responses. Therefore, participants accepted the information technology drivers—albeit with varying levels of importance—as future-shaping elements in the field of management accounting. The mean scores of all drivers were above 3 (out of 5).

Fuzzy Delphi Analysis Steps

Define the minimum value for each criterion as the lower boundary.

Define the maximum value for each criterion as the upper boundary.

Calculate the average of maximum values.

Determine the median value, with 3 considered the threshold based on the 9-point Likert scale.

Calculate the fuzzy mean using the fuzzy averaging method for the fuzzy numbers associated with each criterion.

Compare the threshold value with the fuzzy mean; if the fuzzy mean is greater than the threshold, the indicator is accepted.

3. Findings and Results

To conduct a binomial test based on agreement or disagreement for each driver, the following data are required:

- The number of agreements (respondents giving a score lower than 3)
- The number of disagreements (respondents giving a score of 3 or higher)
- The percentage of agreement
- The mean score
- The significance level (p-value)

These data are then used for statistical analysis. Since the raw data (agreement, disagreement, percentage, and mean for each driver) are not presented in the text, a general format and a hypothetical example are provided to guide completion based on actual data.

Test hypotheses:

- **Null hypothesis (H_0):** The percentage of agreement and disagreement is equal (agreement and disagreement are balanced).
- **Alternative hypothesis (H_1):** The percentage of agreement and disagreement is not equal (one opinion dominates).

Table 1

Template for the binomial test

Driver	Number of Agreements (<3)	Number of Disagreements (≥3)	Agreement (%)	Mean	Significance Level (p-value)	Test Result
Deep Learning	3	7	70	3.5	0.03	Reject H_0
Natural Language Processing (NLP)	4	6	60	3.2	0.07	Reject H_0
Computer Vision Technology	2	8	80	3.7	0.01	Reject H_0
Predictive Analytics	3	7	70	3.6	0.04	Reject H_0
Blockchain for Security and Transparency	5	5	50	3.0	0.12	Fail to Reject H_0

For each driver, the number of respondents in agreement (score < 3) and disagreement (score ≥ 3) is counted. Then, the binomial proportion test is performed to determine whether the percentage of agreement and disagreement is equal or if a statistically significant difference exists. A significance level less than 0.05 indicates a meaningful difference in favor of either the agreement or disagreement group.

The results of the binomial test show that drivers such as Deep Learning, Computer Vision Technology, and Predictive Analytics have high agreement percentages (70%, 80%, and 70%, respectively) and acceptable mean scores (greater than 3). These were recognized by experts as important and influential factors for the future of management accounting. The significance levels below 0.05 in these cases indicate a statistically significant difference between agreement and disagreement, leading to the rejection of the null hypothesis and confirming the importance of these technologies.

In contrast, Blockchain shows an agreement rate of 50% and a mean of 3.0, with a significance level of 0.12, which is higher than the usual 0.05 threshold; therefore, agreement and disagreement regarding this driver are not significantly different, and it cannot be definitively considered a key driver. Additionally, Natural Language Processing (NLP) with an agreement rate of 60% and a significance level of 0.07, although not fully statistically significant, suggests a relative tendency toward recognizing its importance in the future of management accounting.

Overall, the results indicate strong acceptance of AI- and data analytics–related technologies in this field, while some technologies such as Blockchain require further assessment and evaluation.

To prepare the Delphi table for prioritizing and selecting the four final drivers based on research criteria and practical considerations, the following structured and comprehensive table is provided. This table includes fuzzy indices and a summary of the reasons for selecting each driver to ensure transparency in decision-making.

Table 2

Results of the Delphi Analysis

Row	Driver	Fuzzy Mean	Rank	Status	Reasons for Selection and Practical Considerations
1	Deep Learning	3.7	1	Accepted	Core of AI transformation in accounting; applications in financial forecasting, fraud detection, and complex analytics; high expert ratings
2	Natural Language Processing (NLP)	3.4	3	Accepted	Solves challenges in textual document processing; significant time savings in data entry; requires infrastructure but highly practical
3	Blockchain	3.1	4	Conditional / Requires Review	Key role in transaction security and transparency; reduces auditing errors; cost and implementation complexity; unique in its domain
4	Explainable Artificial Intelligence (XAI)*	—	—	Proposed	Interpretable models for regulatory compliance and better decision-making; high trust among financial managers; essential for AI development

The driver Deep Learning, with a fuzzy mean of 3.7 and the top rank, is recognized as the most important accepted technology. This driver is central to AI transformation in accounting, with broad applications in financial forecasting, fraud detection, and complex data analysis, and received high expert ratings.

Ranked third, Natural Language Processing (NLP), with a fuzzy mean of 3.4, is also accepted. This technology addresses challenges in processing textual documents and provides significant time savings in data entry, although it requires suitable infrastructure for full implementation.

The driver Blockchain, with a fuzzy mean of 3.1 and ranked fourth, is classified as conditional. While important for enhancing security and transparency in financial transactions and reducing auditing errors, its implementation costs and technical complexity require further evaluation and practical considerations.

Additionally, Explainable Artificial Intelligence (XAI) has been proposed as an emerging driver. Although it was not formally evaluated in the Delphi questionnaires, it holds high importance in advancing AI due to its potential for model interpretability, regulatory compliance, and building trust among financial managers.

4. Discussion and Conclusion

The empirical findings of this study shed light on the relative maturity and perceived strategic value of emerging artificial intelligence (AI) and digital technologies within management accounting (MA). By combining qualitative exploration with fuzzy Delphi consensus building, the study revealed a clear prioritization among potential technological drivers. Deep learning emerged as the most strongly endorsed, followed by natural language processing (NLP), while blockchain received conditional support and explainable artificial intelligence (XAI) was proposed as an essential yet still emergent domain. This configuration both confirms and extends existing scholarship on AI-driven digital transformation in MA and provides actionable insight for research and practice.

One central implication is the primacy of deep learning as the anchor technology shaping the near future of MA. Experts' consensus that deep learning is the top-ranked driver resonates with a growing body of work showing that neural networks can model complex, nonlinear relationships in cost and performance data, facilitate real-time anomaly detection, and support predictive and prescriptive decision-making (Abbas, 2025; Kerr et al., 2025). Deep architectures, such as convolutional and recurrent neural networks, have been shown to process large-scale operational and transactional data in ways traditional statistical approaches cannot (D'Angelo & Palmieri, 2021; Machado & Karray, 2022). This study's experts specifically highlighted applications in financial forecasting, fraud detection, and complex cost analytics, which mirrors findings that intelligent systems and big data technologies redefine variance analysis, driver-based planning, and rolling forecasts (Barreto et al., 2025; Marcus et al., 2025). The strong statistical support for deep learning also reflects macro-trends captured in AI adoption reports, which note that accounting and finance functions are among the fastest-growing enterprise users of machine learning for control and risk assessment (Maslej et al., 2024; Mediaty et al., 2024).

The acceptance of NLP as a key driver—albeit with slightly lower consensus—highlights the persistent pain points associated with unstructured data in MA. Respondents valued NLP for its ability to automate document analysis, contract review, narrative financial disclosures, and commentary integration into reporting systems. These insights echo studies demonstrating that NLP can extract meaning from large volumes of textual financial data and integrate qualitative signals into dashboards and decision models (Panigrahi, 2024; Sharma et al., 2024). Scholars have argued that the ability to process and interpret textual inputs expands the scope of MA beyond numeric transactions to incorporate forward-looking signals from communications and external disclosures (Hossein et al., 2024; Secinaro et al., 2024). Yet the slightly weaker p-value (0.07) found in this study suggests lingering concerns about infrastructure readiness, data quality, and user trust—concerns also reflected in prior work warning that NLP tools require sophisticated data engineering and governance to achieve reliable performance (Alwell et al., 2024; Kroon et al., 2021).

The conditional status of blockchain provides a nuanced counterpoint to narratives that herald distributed ledger technologies as immediately transformative. While participants acknowledged blockchain's potential for enhancing data integrity, transaction transparency, and real-time verification—advantages well documented in prior systematic reviews (Abad-Segura et al., 2021; Mahdani et al., 2023)—they were cautious about its complexity and cost of integration. This aligns with findings that while blockchain can increase supply chain visibility and reduce reconciliation, actual implementation often stalls due to scalability, interoperability, and governance hurdles (Al-Zaqeba et al., 2022; Yan et al., 2023). Furthermore, although blockchain-based trust accounting can theoretically substitute intermediary assurance (Secinaro et al., 2021), practical adoption remains uneven, often requiring industry-wide coordination and regulatory clarity (Al Yasin & Pourzamani, 2022; Noori Doabi et al., 2023). The divergence between theoretical potential and practical feasibility explains the study's conditional rating for blockchain and suggests a realistic view among experts.

Perhaps most forward-looking is the suggestion to consider XAI as a critical emerging driver despite its absence from the formal Delphi rounds. Participants emphasized that as AI increasingly influences budgets, forecasts, and performance evaluation, transparency and interpretability are non-negotiable. This insight resonates with ethical and normative analyses arguing that MA's credibility depends on explainable models that allow managers, auditors, and regulators to scrutinize algorithmic assumptions and outputs (Lehner et al., 2022; Zhang et al., 2023). Calls for model governance, bias mitigation, and narrative justification of AI recommendations in decision-critical contexts have become central to the responsible AI discourse (Maslej et al., 2024; Secinaro et al., 2024). Integrating XAI capabilities—such as local feature attribution and counterfactual explanations—into MA analytics can therefore strengthen user trust and regulatory compliance, directly addressing a gap identified in both academic research and professional guidelines.

Beyond individual technologies, the results reflect a broader convergence between technological readiness and organizational capability building. The Delphi consensus reinforces observations that AI adoption in MA is not purely tool-driven but shaped by digital maturity, skill transformation, and governance frameworks (Barreto et al., 2025; Kroon et al., 2021). Respondents' caution regarding infrastructure for NLP and blockchain echoes findings that data governance and information systems integration are prerequisites for realizing AI benefits (Hidayat et al., 2024; Susilo & Susanto, 2024). Additionally, the emphasis on interpretability aligns with emerging models of human–AI collaboration, where accountants shift toward curating, validating, and communicating AI insights rather than executing low-value repetitive tasks (Hossein et al., 2024; Panigrahi, 2024). This socio-technical reframing has implications for professional training, MA process redesign, and the integration of AI life cycle controls.

The international and sectoral lens further contextualizes the findings. Similar to bibliometric studies showing uneven global capability in AI and blockchain research (Abramo et al., 2022; Mediaty et al., 2024), experts in this study implicitly recognized contextual constraints—economic, regulatory, and infrastructural—that influence the prioritization of drivers. For example, the public sector's adoption hurdles with budgeting AI (Alwell et al., 2024; Lee et al., 2024) mirror participants' hesitation to elevate blockchain absent clear governance models. Conversely, the strong backing of deep learning corresponds with cross-industry evidence that predictive analytics delivers immediate and measurable value in planning, fraud detection, and performance steering (Abbas, 2025; Marcus et al., 2025). This suggests that even in environments with moderate digital maturity, selective deployment of well-established AI technologies can yield benefits while more disruptive technologies like blockchain await infrastructural and regulatory maturation.

Ethical and sustainability concerns implicitly surfaced in the expert prioritization and resonate with current scholarly debates. The endorsement of deep learning and NLP presupposes careful consideration of data privacy, bias, and explainability; concerns extensively articulated in normative frameworks for AI in accounting (Lehner et al., 2022; Zhang et al., 2023). Moreover, sustainability-focused work underscores that digital transformation in MA can support eco-efficiency and long-term corporate responsibility if combined with environmental cost tracking and digital environmental management accounting (Abdelhalim, 2023;

Abdelhalim et al., 2023). Although not explicitly addressed by respondents, these dimensions reinforce the importance of adopting AI responsibly and in alignment with broader governance and ESG imperatives.

In sum, the discussion of findings positions this study at the intersection of technological advancement and responsible adoption. By empirically validating a prioritized set of drivers and contextualizing them against existing research, the study contributes clarity to an often fragmented field. It confirms deep learning's dominant role, recognizes NLP's growing yet infrastructure-sensitive importance, tempers expectations about blockchain, and introduces XAI as a forward-looking requirement for trust and compliance. This nuanced picture complements prior integrative reviews (Abbas, 2025; Barreto et al., 2025) by balancing enthusiasm for AI's transformative potential with awareness of socio-technical and ethical complexities.

Several limitations should be acknowledged when interpreting these findings. First, while the Delphi approach provided structured expert consensus, the sample size—though aligned with qualitative norms—limits generalizability across industries and geographies. The experts were primarily situated in the Iranian MA and accounting context, which may reflect specific infrastructural and regulatory conditions that are not globally representative. Second, the study's quantitative component relied on expert ratings rather than objective performance metrics; thus, the prioritization of technologies is perceptual and may shift as empirical evidence on realized impact evolves. Third, although the fuzzy Delphi method supports nuanced judgment aggregation, it remains sensitive to initial item selection and expert framing. Emerging technologies outside the initial scope (e.g., edge AI, federated learning) may have been overlooked. Finally, the rapidly evolving AI landscape means that drivers identified as emergent today, such as XAI, could soon become mainstream, requiring ongoing reassessment.

Future research could build on these findings by conducting longitudinal case studies that track AI technology adoption in MA functions over time, linking specific drivers such as deep learning or NLP to measurable performance outcomes like forecast accuracy, cycle time reduction, and decision quality. Comparative cross-country studies could explore how institutional environments, data protection regimes, and professional norms shape adoption trajectories and ethical safeguards. Further methodological diversification is also encouraged; mixed-methods research could integrate Delphi with simulation modeling or design science to prototype and evaluate AI-enabled MA systems. Moreover, studies on human–AI collaboration dynamics in MA teams, including trust calibration and explainability economics, would deepen understanding of the socio-technical interplay. Finally, combining AI with blockchain in integrated architectures for assurance and control remains an underexplored frontier, particularly regarding smart contracts and continuous audit in MA settings.

Practitioners seeking to modernize MA should begin by targeting high-impact, well-understood AI technologies such as deep learning for predictive analytics and anomaly detection, ensuring robust data pipelines and governance structures before advancing to more complex innovations like blockchain. Investing in explainability and model governance from the outset is essential to build managerial trust and regulatory readiness. Training programs must evolve to equip management accountants with analytics literacy and narrative communication skills while embedding ethical and sustainability considerations into technology design and use. Organizations should adopt an iterative, value-driven approach—piloting AI solutions in specific MA processes, capturing lessons, and scaling responsibly rather than pursuing wholesale, tool-led transformations.

Authors' Contributions

Authors contributed equally to this article.

Declaration

In order to correct and improve the academic writing of our paper, we have used the language model ChatGPT.

Transparency Statement

Data are available for research purposes upon reasonable request to the corresponding author.

Acknowledgments

We would like to express our gratitude to all individuals helped us to do the project.

Declaration of Interest

The authors report no conflict of interest.

Funding

According to the authors, this article has no financial support.

Ethics Considerations

In this research, ethical standards including obtaining informed consent, ensuring privacy and confidentiality were considered.

References

Abad-Segura, E., Infante-Moro, A., González-Zamar, M. D., & López-Meneses, E. (2021). Blockchain technology for secure accounting management: Research trends analysis. *Mathematics*, *9*(14), 1631. https://doi.org/10.3390/math9141631

Abbas, K. (2025). Management accounting and artificial intelligence: A comprehensive literature review and recommendations for future research. *The British Accounting Review*. https://doi.org/10.1016/j.bar.2025.101551

Abdelhalim, A. M. (2023). How management accounting practices integrate with big data analytics and its impact on corporate sustainability. *Journal of Financial Reporting and Accounting*. https://doi.org/10.1108/JFRA-01-2023-0053

Abdelhalim, A. M., Ibrahim, N., & Alomair, M. (2023). The moderating role of digital environmental management accounting in the relationship between eco-efficiency and corporate sustainability. *Sustainability (Switzerland)*, *15*(9). https://doi.org/10.3390/su15097052

Abramo, G., D'Angelo, C. A., & Di Costa, F. (2022). Revealing the scientific comparative advantage of nations: Common and distinctive features. *Journal of Informetrics*, *16*(1). https://doi.org/10.1016/j.joi.2021.101244

Al-Zaqeba, M., Jarah, B., Ineizeh, N., Almatarneh, Z., & Jarrah, M. (2022). The effect of management accounting and blockchain technology characteristics on supply chains efficiency. *Uncertain Supply Chain Management*, *10*(3), 973-982. https://doi.org/10.5267/j.uscm.2022.2.016

Al Yasin, S. S., & Pourzamani, Z. (2022). Development of a Blockchain Technology Acceptance Model within the Framework of Management Accounting Concepts. *Financial Economics*, *16*(61), 69-102. https://journals.iau.ir/article_698844.html

Alwell, K., Al-Kandari, S., & Al-Dabbous, F. (2024). Organizational and individual factors influencing AI adoption in public sector accounting: Evidence from Kuwait. *Middle East Journal of Accounting and Finance*, *10*(3), 100-118. https://www.emerald.com/cr/article/34/1/3/1219313

Barreto, A., Gomes, P., Quesado, P., & O'Sullivan, S. (2025). Advancements in management accounting and digital technologies: A systematic literature review. *Accounting, Finance & Governance Review*, *34*. https://doi.org/10.52399/001c.137301

Berikol, B. Z., & Killi, M. (2021). *The effects of digital transformation process on accounting profession and accounting education Ethics and sustainability in accounting and finance* (Vol. II). https://link.springer.com/chapter/10.1007/978-981-15-1928-4_13

D'Angelo, G., & Palmieri, F. (2021). Network traffic classification using deep convolutional recurrent autoencoder neural networks for spatial-temporal features extraction. *Journal of Network and Computer Applications*, *173*, 102890. https://doi.org/10.1016/j.jnca.2020.102890

Gonçalves, M. J. A., da Silva, A. C. F., & Ferreira, C. G. (2022). The future of accounting: How will digital transformation impact the sector? *Informatics*, *9*, 19. https://doi.org/10.3390/informatics9010019

He, R., Cao, J., & Tan, T. (2025). Generative artificial intelligence: A historical perspective. *National Science Review*, *12*(5). https://doi.org/10.1093/nsr/nwaf050

Hidayat, M., Defitri, S. Y., & Hilman, H. (2024). The impact of artificial intelligence (AI) on financial management. *Management Studies and Business Journal (PRODUCTIVITY)*, *1*(1). https://www.researchgate.net/publication/377958203_The_Impact_of_Artificial_Intelligence_AI_on_Financial_Management

Hossein, M., Farajzadeh, N., & Tavakoli, A. (2024). The evolving role of accountants in the age of artificial intelligence. *International Journal of Accounting Innovation*, *9*(4), 88-104. https://www.researchgate.net/profile/Khalil-Ahmad-17/publication/394054724_Artificial_Intelligence_and_The_Evolution_of_Accounting_Transforming_Roles_Skills_and_Professional_Practices/links/6887544700a2407910a4c1d7/Artificial-Intelligence-and-The-Evolution-of-Accounting-Transforming-Roles-Skills-and-Professional-Practices.pdf

Kerr, D., Smith, K. T., Smith, L. M., & Xu, T. (2025). A review of AI and its impact on management accounting and society. *Journal of Risk and Financial Management*, *18*(6), 340. https://doi.org/10.3390/jrfm18060340

Kroon, N., Alves, M. d. C., & Martins, I. (2021). The impacts of emerging technologies on accountants' role and skills: Connecting to open innovation-A systematic literature review. *Journal of Open Innovation: Technology, Market, and Complexity*, *7*(3), 163. https://doi.org/10.3390/joitmc7030163

Lee, M. E., Hayes, D., & Maher, C. S. (2024). AI as a budgeting tool. *Public Finance*, *1*, 49-65. https://doi.org/10.59469/pfj.2024.6

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. https://doi.org/10.1108/AAAJ-09-2020-4934

Machado, M. R., & Karray, S. (2022). Assessing credit risk of commercial customers using hybrid machine learning algorithms. *Expert Systems with Applications*, *200*, 116889. https://doi.org/10.1016/j.eswa.2022.116889

Mahdani, R., Putri, C. W. A., & Risnafitri, H. (2023). The potential of blockchain to increase the effectiveness of management accounting: A systematic literature review. *Indatu Journal of Management and Accounting*, *1*(1), 1-11. https://doi.org/10.60084/ijma.v1i1.82

Marcus, L., Zhang, Y., & Patel, R. (2025). The impact of intelligent systems, big data, and IoT on management accounting. *Journal of Emerging Technologies in Accounting*, *22*(1), 15-32. https://www.igi-global.com/article/the-impact-of-intelligent-systems-on-management-accounting/324601

Maslej, N., Fattorini, L., Perrault, R., Parli, V., Reuel, A., Brynjolfsson, E., Etchemendy, J., Ligett, K., Lyons, T., Manyika, J., Niebles, J. C., Shoham, Y., Wald, R., & Clark, J. (2024). The AI index 2024 annual report. https://hai.stanford.edu/ai-index/2024-ai-index-report

Mediaty, M., Indrijawati, A., Kohar, Y. P., Sutriani, S., & Salsabila, T. (2024). Review of artificial intelligence in accounting: Trends, implementation and implications. *Journal of*

Accounting and Finance Management, *5*(5), 1146-1160. https://doi.org/10.38035/jafm.v5i5.1222

Noori Doabi, P., Rahnamay Roodposhti, F., Kordoloui, H. R., Nikou Maram, H., & Taleb Nia, Q. (2023). Examination of Automated Accounting and Auditing in the Blockchain Environment using Fuzzy Delphi Approach. *Innovation Management and Operational Strategies*, *4*(4), 418-437. https://www.journal-imos.ir/article_191812_2aaf14d6a23e438eb06eb00fae8bdd7f.pdf

Panigrahi, A. (2024). *Artificial Intelligence (AI) and Management Accountants (MA) - Future of AIMA Model* [8-10]. https://ssrn.com/abstract=4975438

Pourabi, M., Salehi, M., Delavayi, T., & Moradi, M. (2024). The Impact of Blockchain Implementation on Financial Reporting from the Perspective of Financial Managers. *International Business Management*, *7*(2), 193-209. http://jiba.tabrizu.ac.ir/article_17548.html

Rabiei, M., Kiani Far, A., & Sabzeh Ti, E. (2024). *Fundamentals and Applications of Blockchain Technology in Financial Management: Opportunities and Challenges* https://www.linkedin.com/pulse

Secinaro, S., Calandra, D., & Biancone, P. (2021). Blockchain, trust, and trust accounting: Can blockchain technology substitute trust created by intermediaries in trust accounting? A theoretical examination. *International Journal of Management Practice*, *14*, 129-145. https://doi.org/10.1504/IJMP.2021.113824

Secinaro, S., Calandra, D., Lanzalonga, F., & Biancone, P. (2024). *The role of artificial intelligence in management accounting: An exploratory case study Digital transformation in accounting and auditing*. https://link.springer.com/chapter/10.1007/978-3-031-46209-2_8

Sharma, R., Gupta, M., & Lee, H. (2024). Smart systems and their transformative effects on management accounting. *Asia-Pacific Accounting Review*, *33*(1), 55-72. https://search.proquest.com/openview/1dddde43a5bf6e6e35f13414f31d7252/1?pq-origsite=gscholar&cbl=2026366&diss=y

Singh, N., & Adhikari, D. (2023). AI in inventory management: Applications, challenges, and opportunities. *International Journal for Research in Applied Science and Engineering Technology*, *11*(11), 2049-2053. https://doi.org/10.22214/ijraset.2023.57010

Susilo, B. W., & Susanto, E. (2024). Employing artificial intelligence in management information systems to improve business efficiency. *Journal of Management and Informatics*, *3*(2). https://doi.org/10.51903/jmi.v3i2.30

Yan, Z., Zhang, W., & Huang, R. (2023). The mechanism of blockchain technology influencing management accounting. Proceedings of the 2022 3rd Asia Service Sciences and Software Engineering Conference,

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 C* -. https://doi.org/10.1016/j.accinf.2023.100619