



**THE ROLE OF ARTIFICIAL INTELLIGENCE IN TRANSFORMING MANAGEMENT
ACCOUNTING PRACTICES: AUTOMATION, ANALYTICS, AND STRATEGIC
DECISION-MAKING IN MODERN ORGANIZATIONS**

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Abstract

Artificial intelligence (AI) is changing how organizations produce and use the information they rely on to plan, control, and allocate resources. Accounting scholarship has documented many individual pieces of this shift automation projects, predictive-analytics applications, professional skill change but the pieces are rarely put together. This paper works through what happens when they are. Drawing on accounting and information-systems research published mainly between 2017 and 2026, it argues that AI's real significance for management accounting is not the automation of individual tasks but the reshaping of the whole pathway from raw organizational data to strategic action. That pathway is described here as a progression: AI-enabled process automation feeds into integrated information and advanced analytics, which in turn support decision intelligence but only where human judgement remains actively involved. Machine learning extends what management accounting can predict and measure; generative AI changes how accountants interact with information in the first place. Neither guarantees better decisions on its own. Data quality, governance, explainability, professional competence, and organizational readiness all determine whether AI output becomes usable managerial knowledge, and the paper's central contribution is a human–AI decision-intelligence framework built around that condition. The framework treats automation and analytics as necessary but insufficient: value is created only when technological capability is filtered through professional judgement operating inside adequate governance.

Keywords: artificial intelligence; management accounting; intelligent automation; machine learning; generative AI; analytics; decision intelligence; strategic decision-making.

Introduction

Management accounting has always been an internal information function, the part of the organization responsible for turning transactions and operations into something managers can plan, budget, and make decisions with. For most of its history that meant working with structured financial data collected, processed, and reported in fairly fixed cycles. That configuration is now under pressure. Firms generate financial and non-financial data continuously, through enterprise systems, digital transactions, customer platforms, and operational technology that did not exist in anything like its current form a decade ago, and accountants increasingly have the tools to combine this data and subject it to classification, prediction, and language-based analysis rather than treat it as separate, incompatible streams (Moll & Yigitbasioglu, 2019). Whether this amounts to more than a further stage of accounting, automation is an open question in the literature, but the recent evidence leans toward yes. Abbas (2026) reviewed ninety-one studies on digitalization and AI in management accounting and concludes that these technologies are reshaping not just individual tasks but accounting's organizational structures and its relationship to the rest of the firm. Working from a

different angle topic modelling across 930 peer-reviewed abstracts. Murphy et al. (2024) find eleven distinct research clusters in the accounting-and-AI literature, which is itself evidence that the field has moved well past the older question of whether software will replace accountants.

Work on intelligent automation tends to stay close to efficiency and process redesign; work on machine learning stays close to prediction; work on generative AI has drifted toward questions of knowledge work and professional identity. Read separately, none of these strands captures what is actually at stake organizationally. The question worth asking is not whether a given accounting task can be automated, or whether a model beats a manager at forecasting, it is how AI changes the route from accounting data to managerial understanding, and from there to action. That route matters because speed is not the same thing as quality: an AI system can process data quickly and surface patterns a human analyst would likely miss, but whether the resulting output is actually useful still depends on data quality, system governance, organizational context, and whether managers are willing to question a machine-generated recommendation rather than simply accept it. Zhang et al. (2025), while interviewing representatives from forty-one companies about AI adoption in managerial accounting, found that institutional and individual factors both shape whether adoption succeeds — confirming that technical capability on its own is not sufficient, and pointing toward the argument this paper develops.

AI, on that argument, is moving management accounting from an information-processing function toward a decision-intelligence capability, and it is doing so by connecting three things: intelligent automation, advanced analytics, and human judgement. Automation changes how information is produced; analytics changes what can be learned from it; judgement is what turns an analytical output into something an organization can actually act on — none of the three does the useful work alone. What follows synthesizes recent accounting and information-systems scholarship around these three dimensions, examines the governance and professional competencies needed to convert AI capability into organizational value, and closes with a conceptual framework linking AI-enabled accounting to strategic decision intelligence.

Conceptualizing Artificial Intelligence in Management Accounting

“Artificial intelligence” covers a lot of ground — computational approaches that let systems learn, recognize patterns, predict, classify, process language, and support decisions. Within accounting it should not be treated as one technology with one label. Machine learning, natural language processing, intelligent automation, predictive modelling, and generative AI are functionally different tools, and Murphy et al.'s (2024) eleven-cluster map of the accounting-and-AI literature makes that variety visible: the field spans efficiency, fraud detection, automation, and informational reliability, not just bookkeeping automation as commonly assumed. Davenport and Ronanki (2018), writing for a general business audience rather than an accounting one, propose a simpler way to sort AI applications by what they are for: automating a process, generating insight from data, or engaging with people through language. The distinction transfers reasonably well to management accounting, where the same three functions recur — automating reconciliation and reporting, generating predictive and diagnostic insight, and, more recently, engaging users through generative interfaces.

Management accounting itself is concerned with producing and using information for planning, control, performance evaluation, resource allocation, and decision-making, so the intersection with AI is broader than automating routine processing. It touches how managerial





information gets generated, how organizational performance gets interpreted, and what decisions follow. Ranta et al. (2023) identify four specific opportunities for machine learning in this space: better prediction, the use of textual and unstructured data that conventional accounting analysis ignores, new performance measures, and explainable-AI techniques that make model outputs interpretable rather than opaque. Their broader point is that management accounting no longer needs to confine itself to structured financial data — a shift also traced by Rikhardsson and Yigitbasioglu (2018) in their review of business intelligence and analytics research, which finds relatively thin empirical coverage of how these tools actually change management-accounting tasks despite growing practitioner interest. Taken together, this literature suggests a working definition: AI-enabled management accounting is the integration of intelligent computational technologies into accounting processes to improve how information is acquired, processed, analysed, interpreted, and communicated for organizational planning and decision-making.

Theoretical Foundations of AI-Driven Management Accounting Transformation

Technology-Organization-Environmental Perspective

Why do some organizations get real value from AI while others struggle? The Technology–Organization–Environment (TOE) framework offers one answer: adoption success depends on more than whether a technology can technically perform a task (Tornatzky & Fleischer, 1990). It also depends on organizational readiness, available skills, management support, existing infrastructure, and the wider competitive and regulatory environment. Zhang et al.'s (2025) interview study of forty-one companies fits this picture closely — institutional and individual adoption factors both mattered, and technological capability alone did not predict success. The framework is a natural fit for management accounting specifically because AI systems typically sit on top of existing ERP systems, accounting databases, and data governance arrangements; an organization with fragmented systems and weak governance is likely to get much less out of AI than one with integrated, reliable infrastructure, whatever the sophistication of the model involved.

Dynamic Capabilities Perspective

Another useful lens treats AI as a resource organizations use to sense change, interpret information, and reconfigure their own activities — the dynamic capabilities view (Teece et al., 1997). Management accounting has always supported these functions through budgets, variance analysis, and forecasts, but AI changes their speed and scale. Rather than waiting for the next periodic report to surface a problem, organizations can increasingly draw on continuously updated data and predictive models to catch emerging patterns as they form. Yoshioka and Ishii (2025) build a framework along these lines, integrating generative AI with data-science techniques to support simulation, prediction, and scenario analysis inside management accounting, and arguing that this combination strengthens real-time decision support in ways a historically oriented reporting cycle simply cannot. Seen this way, AI's strategic value is less about cutting manual work and more about improving an organization's capacity to notice and respond to change before it becomes a problem.

Technology Acceptance and Individual-Level Adoption

Organizational readiness is only part of the story; individual accountants still have to decide whether to use the tools in front of them. The Technology Acceptance Model (TAM) explains that decision through two constructs — perceived usefulness and perceived ease of use (Davis, 1989) —



and both recent studies cited in this paper apply it directly to accounting. Ross and Zhang (2025), surveying 136 practitioners about ChatGPT, find perceived usefulness, ease of use, and personal innovativeness all positively associated with adoption, while perceived risk works in the opposite direction and, notably, trust does not predict use once those other factors are accounted for. Zhang et al. (2025) find a parallel pattern at the organizational level, where perceived usefulness of AI outputs and ease of use of AI tools sit alongside institutional factors as adoption drivers. Together these findings are a reminder that AI's value to management accounting is filtered twice — once through organizational governance, and again through what individual accountants actually believe about the tools they are being asked to use.

AI and the Changing Architecture of Management Account

AI is not one account technology but a family of them — machine learning, natural-language processing, intelligent automation, predictive modelling, generative AI — each with different applications but a shared capacity to perform or augment work that used to require a person: recognizing patterns, processing information, communicating results. Put together, they let accounting information be processed faster and, in principle, with more analytical range than before.

The practical effect is a change in structure, not just speed. Management accounting has traditionally run through a fairly linear sequence — collect, process, report, interpret — that is inherently backward-looking: it explains what already happened. What AI introduces looks more like a loop than a line: data generation feeds intelligent processing, which feeds continuous analysis, which feeds prediction and scenario development, which is interpreted by people, acted on strategically, and generates new data that restarts the cycle. Rikhardsson and Yigitbasioglu (2018) describe a version of this shift in their review of business intelligence and analytics research, identifying five recurring themes — including data quality and organizational readiness — that determine whether firms actually realize the loop's benefits rather than just building the technology.

AI-Enabled Automation: From Process to an Enabling Layer

Automation is the most visible face of AI in management accounting, and for good reason — a large share of the work involves collecting, classifying, reconciling, consolidating, validating, and reporting data, much of it repetitive. Enterprise systems already automate a good deal of this; AI adds the ability to recognize patterns, predict, flag anomalies, and handle less structured information than rule-based automation ever could. In practice this shows up in three overlapping areas. Intelligent data processing extracts and classifies transactional and operational data from enterprise systems and unstructured documents with less manual intervention than conventional automation requires. Continuous exception detection flags deviations — unusual expenditure, a control breach, a reconciliation gap — as they happen rather than at the next scheduled review. And automated reporting assembles routine management reports and variance summaries with minimal manual compilation, which is really the point: it frees professional time for interpretation rather than compilation.

Robotic process automation (RPA) is the clearest bridge between conventional accounting systems and this more AI-enabled version of automation. Interview evidence from Big Four accounting firms shows RPA implemented across a wide range of accounting processes, with firms reporting substantial gains in processing time (Cooper et al., 2019); a follow-up survey of the same



firms found that both leaders and lower-level staff generally viewed RPA's effect on the profession positively, though the two groups did not always agree on whether it improved job satisfaction (Cooper et al., 2022). Kokina and Davenport (2017) had already flagged this trajectory a few years earlier, arguing that automation was beginning to change what auditors and accountants actually spend their time doing, well before generative AI entered the picture.

The more critical literature complicates this picture usefully. Eulerich et al. (2024a) interviewed practitioners about RPA specifically to surface its problems rather than its benefits, and identified five recurring ones: RPA gets used as a quick fix for underlying system weaknesses rather than a real solution; it introduces control and security risks that are easy to overlook; its true cost is routinely underestimated; its governance is genuinely difficult; and heavy reliance on it can erode institutional process knowledge. A companion paper from the same authors proposes internal-control and governance principles built specifically for RPA environments, on the reasoning that governance frameworks designed for manual processes do not transfer cleanly (Eulerich et al., 2024b). Zhang et al. (2023), looking at the ethics of AI in managerial accounting more broadly, raise a related set of concerns — data security, privacy, misuse, accountability, transparency — that automation projects tend to assume away rather than address.

The pattern across this evidence is fairly consistent: automating a process is not the same as transforming it. A poorly designed process automated at speed is still a poorly designed process, just a faster one. For management accounting specifically, this has three practical implications. Automation can make information more timely, since data that used to require extensive manual handling becomes available faster. It can shift where professional effort goes — less time on repetitive processing, more on analysis and communication. And it can increase the sheer volume and frequency of information available to managers, which sets up the next stage of the argument: analytics. Automation, in other words, is not really the destination of AI adoption. It is closer to infrastructure for what comes after it.

From Accounting Data to AI- Enabled Analytics

AI's strategic significance becomes clearer once automation is paired with genuine analytics. Management accounting has long relied on descriptive and diagnostic techniques — variance analysis, budgeting, cost analysis, performance reporting — but these are essentially retrospective: they explain what happened and identify where results deviated from expectations. Machine learning changes the direction of travel, because it can process large, messy, heterogeneous datasets and surface relationships that are not obvious through conventional methods. Ranta et al. (2023) point specifically to predictive analytics, non-traditional data sources, and new approaches to interpretation as the areas where machine learning adds the most; Appelbaum et al. (2017) make a related argument earlier in the literature, proposing a management-accounting data-analytics (MADA) framework that ties business analytics explicitly to the balanced-scorecard tradition rather than treating it as a separate, IT-owned activity. Both point toward the same conclusion — the gain is not just processing more data, but expanding what counts as relevant management-accounting information in the first place.

It helps to think of this as a progression: descriptive analysis (what happened?), predictive analytics (what is likely to happen?), and prescriptive or scenario-based analysis (what would happen under different assumptions?). Historical information stays essential for control and evaluation, but



its usefulness thins out precisely when managers most need to decide under uncertainty — which is exactly where predictive models help, by surfacing emerging trends, likely cost or revenue movements, and risks before they show up in a report. There is now direct empirical evidence that this is not just a theoretical possibility. Ding et al. (2020), working with insurance-industry loss-reserve data, show that machine-learning estimates outperformed the managerial estimates actually reported in financial statements in four of five insurance lines examined — a concrete demonstration that machine learning can outperform human judgement on a specific, well-defined accounting estimation task, even if that result should not be generalized carelessly to every managerial judgement call. Bertomeu et al. (2021) offer a related but distinct example on the diagnostic side, using machine learning across accounting, market, governance, and audit variables to detect and interpret patterns behind ongoing financial misstatements — with the interesting finding that accounting variables alone predict misstatements poorly, and only become useful in combination with audit and market data.

AI also loosens the informational boundaries management accounting has traditionally worked within. Conventional systems privilege structured financial data by default; machine learning can bring in operational records, text, and behavioural indicators alongside it, potentially revealing relationships between financial outcomes and operational conditions that a purely financial analysis would miss (Ranta et al., 2023). None of this guarantees better decisions, though. Predictive models inherit the limitations of the data they are trained on, and more complex models can become harder for the people using them to interpret or challenge — which puts a new kind of responsibility on management accountants: not just checking what a model predicts, but why it produces that prediction, how solid the underlying evidence is, and whether the output actually fits the decision at hand.

That responsibility marks a real separation between analytical capability and decision quality. AI can expand what an organization can process, detect, and forecast, and still not improve the decisions that follow — decision quality depends on how analytical output interacts with judgement, organizational objectives, and governance, not on the sophistication of the model alone. The more accurate description of what is happening, then, is not a shift from human analysis to machine analysis but a shift toward analytical complementarity: AI supplies scale, speed, and pattern recognition; accountants supply context, scepticism, and organizational knowledge. Analytical capacity becomes decision value only when both sides are actually present.

Generative AI and the Reconfiguration of Management –Accounting Knowledge Work

Generative AI changes something slightly different — not just what can be done with organizational information, but how accountants interact with it day to day. Earlier analytical systems required navigating fixed interfaces and predefined functions; generative systems let users ask questions in ordinary language and get back summaries, explanations, comparisons, and scenario-based responses, which in principle narrows the gap between a complex information system and the manager trying to get an answer out of it. Yoshioka and Ishii (2025) build this idea into an explicit framework, integrating generative AI with data-science methods to support simulation and real-time scenario analysis in ways a traditional, backward-looking reporting cycle cannot match.

What this looks like in practice, so far, is more modest than the framing suggests. Ross and Zhang (2025), surveying 136 accounting practitioners with follow-up interviews, find limited real



experience with ChatGPT at the time of the study and use concentrated in administrative tasks — though expectations for future value-adding use were considerably higher than current use. The finding that matters most here is that adoption was not explained by availability of the tool; it tracked perceived usefulness, ease of use, personal innovativeness, and perceived risk, with risk perception acting as a genuine brake even where usefulness was recognized. Dong et al. (2024), reviewing the broader ChatGPT-and-LLM literature in accounting and finance, find the research itself clustering around three themes — direct applications, ChatGPT used as a research tool, and questions about what LLM adoption means for professionals and organizations — and note that many of the more interesting questions in the third cluster remain only partly answered. A wider, seventy-plus-author consensus paper on generative conversational AI reaches a similar conclusion from outside accounting specifically: productivity gains are real, but so are risks around accuracy, bias, and the displacement of certain kinds of work, and neither can be assumed away (Dwivedi et al., 2023).

Where generative AI seems most useful for management accounting is as a mediator between complex information and the people who have to act on it — synthesizing information across reports and systems, translating analytical results into something closer to a managerial narrative, comparing assumptions, doing a first pass through documents before a person looks at them properly. None of that amounts to generative AI exercising managerial judgement on its own. A fluent, coherent-sounding response is not the same as an accurate or contextually appropriate one, and that gap is precisely why outputs need to stay subject to verification and professional scrutiny rather than being taken at face value. The accountant's responsibility does not disappear when information generation gets automated — it shifts toward evaluating whether what the system produced is actually credible and relevant.

This has implications for what the profession looks like going forward. As AI takes on more information retrieval, synthesis, and routine knowledge work, what is left for the accountant to contribute concentrates more heavily around interpretation, contextual reasoning, scepticism, communication, and accountability — augmentation rather than substitution, in other words. The accountant increasingly sits between the system and the decision: interrogating outputs, checking them against context, and communicating what matters to the people who actually have to act. If anything, that role is more demanding than the one it replaces, not less.

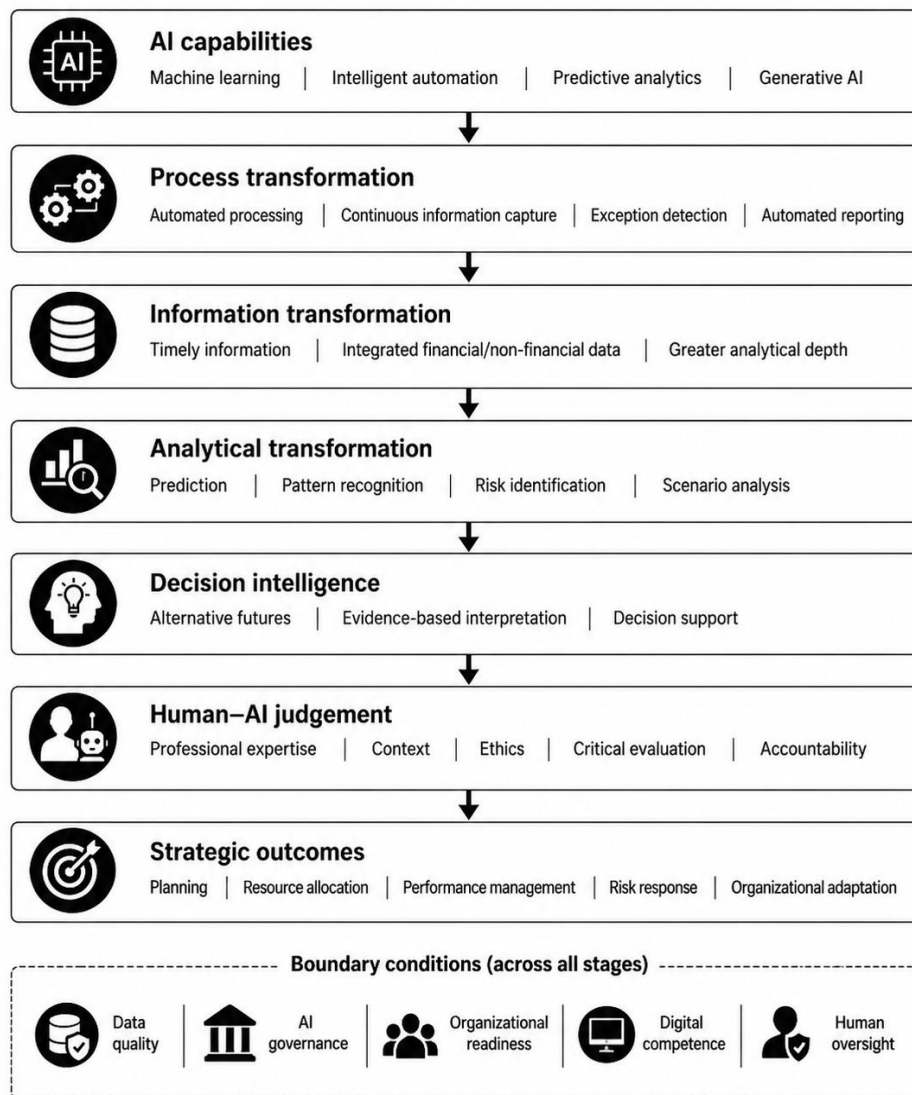
A Conceptual Framework

Figure 1 pulls the argument above into a single framework. It moves from underlying AI capabilities — machine learning, intelligent automation, predictive analytics, generative AI — through process and information transformation into analytical transformation and, eventually, decision intelligence. The important design choice is that the framework does not end at a computational output. Before analytical or predictive insight becomes a strategic outcome, it passes through an explicit human–AI judgement stage — professional expertise, organizational context, ethics, critical evaluation, accountability — and only then feeds into planning, resource allocation, performance management, risk response, and organizational adaptation. Five boundary conditions run underneath every stage of the framework: data quality, AI governance, organizational readiness, digital competence, and human oversight. These are not decorative; they are the specific conditions the evidence reviewed above (Zhang et al., 2025; Kokina et al., 2025) identifies as determining whether any of this actually works in practice. The framework, in short, treats management accounting not as a pipeline AI simply speeds

up, but as a decision-intelligence system where automation and analytics are necessary and clearly insufficient on their own — value only shows up once technological output has been filtered through judgement operating inside adequate governance.



Figure 1. AI-Enabled Management Accounting Decision-Intelligence Framework



Implications

For Modern Organizations

Organizations get more out of AI when they treat it as an integrated organizational transformation rather than a portfolio of separate automation projects — automating a badly designed process just lets its inefficiencies run faster. The RPA evidence is a good illustration: examining underlying processes, controls, and system integration before automating them matters, and control principles built for AI-enabled environments need to be genuinely different from principles built for



manual ones, not adapted from them after the fact (Eulerich et al., 2024b). Management accountants should be involved from the start of this process, precisely because their understanding of how organizational information actually gets generated and used positions them to judge whether a given AI application is meaningful or just impressive. Organizations also need to build human capability alongside the technical infrastructure — AI adoption in managerial accounting is shaped by institutional and individual factors together, not either alone (Zhang et al., 2025) — and AI governance belongs inside management-accounting practice rather than being treated as purely an IT responsibility, since data quality, privacy, cybersecurity, explainability, and human oversight all directly affect whether AI-generated information can actually be trusted (Zhang et al., 2023). The right test for AI adoption, ultimately, is not how many tasks it automates or how much processing time it saves, but the quality of the decisions it makes possible.

For Management Accounting Education and Professional Training

This transformation carries real implications for how accountants are trained. Traditional accounting education is not obsolete — sound knowledge of accounting principles, controls, and organizational decision-making does not stop mattering because AI exists — but it increasingly needs to sit alongside digital, analytical, and strategic capabilities suited to AI-enabled work environments. Moll and Yigitbasioglu (2019) raise a related concern about legitimacy: as more of the accountant's traditional task list gets automated, the profession has to actively demonstrate what its distinctive contribution now is, rather than assume it is self-evident. Bou Reslan and Jabbour Al Maalouf's (2024) survey evidence, showing AI adoption changing accounting skill requirements directly, points toward curricula that cover AI and machine learning literacy, data analytics, predictive modelling, AI governance and data ethics, critical evaluation of AI-generated output, and human–AI collaboration specifically. Ross and Zhang's (2025) finding that perceived risk — not availability — is what actually limits generative-AI adoption among practitioners suggests training should address trust and risk perception directly rather than assuming exposure to the tools is enough on its own. None of this means turning accountants into software engineers. The goal is closer to accountants who understand how AI-generated information is produced well enough to question it when it is wrong, and who can connect what the technology produces to what the organization actually needs.

Future Directions for Research

Several open questions follow from the discussion above. How generative AI actually changes budgeting, forecasting, and strategic planning in day-to-day practice remains under-examined — frameworks for integrating generative AI into management accounting exist (Yoshioka & Ishii, 2025), but evidence of what happens when organizations actually use them is thinner.

The relationship between AI adoption and management accountants' professional identity deserves more direct attention too. The more useful question at this point is probably not whether accounting jobs disappear, but which activities stay human-centred and how professional value gets reconstructed around them once the routine work is gone.

Explainability is a third gap worth naming specifically. Even in the more mature area of AI-enabled auditing, transparency, explainability, and overreliance remain unresolved (Kokina et al., 2025) — which suggests management-accounting research, further behind, has considerable ground still to cover on the same problem.



Comparative work across organization size, industry, and national context would help too, since AI adoption is unlikely to follow one trajectory given how much infrastructure, resources, regulation, and workforce capability vary across these dimensions.

And finally, the field should resist the assumption that more AI adoption automatically means better organizational outcomes. It creates possibilities. It does not guarantee results — those depend on implementation quality, governance, human expertise, and strategic alignment, none of which follow automatically from the technology itself.

Conclusion

AI's effect on management accounting goes well beyond automating routine tasks. Its deeper significance is in how it changes the way accounting information gets generated, analysed, interpreted, and turned into managerial action — a transformation that, on the evidence reviewed here, runs through three connected processes. Automation reduces the burden of repetitive information processing and speeds up how quickly accounting information becomes available. Analytics expands what management accounting can identify, predict, and examine, including in unstructured data conventional methods never touched. Strategic decision support connects these capabilities to the actual concerns of organizational management — scenario analysis, risk assessment, forecasting, more dynamic planning — rather than leaving them as technical capability with no organizational destination.

The management accountant's role changes alongside this, but not in the direction of irrelevance. Routine processing becomes increasingly automatable; professional judgement, contextual interpretation, strategic thinking, communication, and ethical oversight become correspondingly more central to what the job actually is. The recent literature on AI adoption in accounting consistently points the same way — toward changed work and changed skill requirements, not a straightforward replacement of the professional (Bou Reslan & Jabbour Al Maalouf, 2024; Zhang et al., 2025).

None of this supports framing the future of management accounting as humans versus AI. The more accurate frame is **human–AI complementarity**: AI processes information at a scale individuals cannot match, and accountants bring the professional judgement, organizational understanding, and ethical reasoning that a system cannot supply on its own. The organizations that get the most out of AI will probably not be the ones that automate the greatest number of tasks — they will be the ones that integrate automation, analytics, governance, and professional judgement into something that actually functions as a coherent decision-making system. AI is not simply changing how management accounting gets done. It is changing what management accounting is for.

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