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Governing AI in Management Accounting: Evidence from an Emerging Industrial Economy

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Abstract

The increasing use of artificial intelligence (AI) in management accounting offers significant potential for improving information quality while simultaneously raising concerns about accountability and managerial decision discipline, particularly in emerging industrial contexts. This study aims to explore in depth how AI governance is practiced within management accounting systems and how management control mechanisms frame AI use to support accountability and organizational value creation. The study draws on the literature on management accounting digitalization, AI governance, and management control theory. A qualitative case study approach was employed in the Batam industrial area, using semi-structured interviews, internal document analysis, and limited observation, with data analyzed through thematic analysis. The findings indicate that AI is predominantly positioned as decision support rather than a decision driver, enhancing managerial sensemaking while preserving human judgment through decision ownership, review routines, and documentation. These results suggest that the value of AI in management accounting depends less on technological sophistication and more on the maturity of governance and control mechanisms that ensure disciplined and accountable decision-making.

Keywords: *AI Governance, Artificial Intelligence, Management Accounting.*

1. INTRODUCTION

The development of artificial intelligence (AI) has transformed the way organizations manage managerial accounting information through the use of advanced analytics to support strategic planning, control, and decision-making [1]. Globally, business intelligence and analytics are increasingly used in managerial accounting practices to accelerate and refine budgeting, cost management, and performance measurement processes [2]. However, the literature confirms that accelerating data-driven decisions does not automatically improve decision quality if the space for wise judgment is limited and not framed by adequate control mechanisms [3]. Research also shows that analytics and enterprise systems can enhance the usefulness of information for managerial accounting, but simultaneously raise the risk of overreliance and challenges in maintaining decision accountability when organizations rely too heavily on system outputs [4]. Therefore, the contemporary managerial accounting discourse is shifting from mere technology adoption to more substantive questions about how digitalization and AI are transforming control practices and the role of the managerial accounting function [5].

The issue of AI governance in managerial accounting is becoming increasingly crucial in the context of developing countries, as the drive to increase competitiveness often outpaces the regulatory readiness, institutional capacity, and control design necessary for responsible implementation [6]. In this environment, AI and analytics implementations are often geared toward pragmatic outcomes such as process speed, efficiency, and predictive accuracy, while aspects such as trust, transparency, and decision control remain recurring challenges. Field research on data analytics projects in the context of forecasting shows that implementation success is heavily influenced by project governance, clarity of objectives (including explainability), and the leadership role of the control function [7]. In the context of manufacturing and digital data environments, the effectiveness of managerial accounting is determined not only by the availability of data/algorithms, but also by how organizations reimagine their work methods, methods, and control practices to align with the characteristics of digitalization [8]. Thus, the need

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for a control framework that maintains decision discipline and managerial accountability remains an increasingly pressing agenda in modern management control studies [9], [10].

This phenomenon is clearly reflected in Batam, one of Indonesia's most strategic industrial regions, which plays a central role in national manufacturing and export performance. Batam is part of the Indonesia–Malaysia–Singapore Growth Triangle (IMS-GT) and has been designated as a Free Trade Zone, attracting significant foreign direct investment, particularly in electronics, precision manufacturing, and shipbuilding industries. According to Indonesia's investment and industrial statistics, Batam consistently ranks among the top regions for manufacturing investment realization and export contribution, with a strong orientation toward global supply chains. In recent years, the acceleration of industrial digitalization in Batam has been evident through the adoption of Industry 4.0 initiatives, automation systems, and data-driven production management, positioning the region ahead of many other industrial areas in Indonesia in terms of technological integration. This rapid digital transformation, however, is not always matched by equivalent development in managerial control systems and governance structures.

Previous research has demonstrated both the potential and risks of using AI in managerial accounting. Davenport and Ronanki [11] explain that AI analytics can improve the quality of information for decision-making, but has the potential to encourage overreliance when not balanced by managerial judgment. Moll and Yigitbasioglu [2] find that digitalization shifts the role of managerial accountants from information providers to strategic partners, while also requiring more adaptive control system design. Meanwhile, Zhang et al. [12] showed that the application of AI in managerial accounting raises significant ethical risks, including issues of accountability, data security, transparency, and trust in AI output, which in turn can undermine control discipline and decision quality if governance is inadequate.

While all three studies highlight the role of AI in supporting managerial decision-making, these studies have clear similarities and differences. The similarities lie in their focus on AI as a decision-support tool in managerial accounting systems and its implications for decision quality and performance. However, unlike previous studies, which generally focus on the context of developed countries and position AI as a technology or analytics issue, this article places governance and management control as the primary lens of analysis, and examines the context of developing industrial economies characterized by different operational and institutional pressures.

This difference in focus underpins the originality of this study, namely examining how AI is governed in managerial accounting systems to maintain control discipline, accountability, and decision quality. This study not only assesses whether AI is used, but also how management control mechanisms frame the use of AI so that it does not replace, but rather enhances, managerial judgment. Thus, this study expands the managerial accounting literature beyond technology adoption to address governance and decision control issues.

While these studies highlight the role of AI in supporting managerial decision-making, they share both similarities and differences. The similarities lie in their focus on AI as a decision-support tool within managerial accounting systems and its implications for decision quality and performance. However, unlike prior studies, which predominantly focus on developed country contexts and position AI primarily as a technological or analytical issue, this study adopts governance and management control as its primary analytical lens and examines a developing industrial economy characterized by distinct operational and institutional pressures.

This difference in focus underpins the originality of this study, namely examining how AI is governed within managerial accounting systems to maintain control discipline, accountability, and decision quality. This study not only assesses whether AI is used, but also how management control mechanisms frame its use so that it complements rather than replaces managerial judgment. Thus, this study extends the managerial accounting literature beyond technology adoption to address governance and decision control issues.

The urgency of this research is further heightened given that industrial regions such as Batam are at the intersection of rapid technological advancement and uneven institutional readiness. Without adequate AI governance, companies face risks of accelerated yet uncontrolled decision-making, information bias, and erosion of managerial responsibility. Therefore, an empirical understanding of how AI is integrated and governed in managerial accounting is essential for both practitioners and policymakers in developing economic contexts.

Based on this background, this study aims to explore in depth how AI governance is practiced in managerial accounting systems in developing industrial regions. Specifically, it seeks to understand the management control mechanisms employed by organizations to frame AI use, and how these mechanisms shape accountability practices, decision discipline, and organizational value creation in daily operations.

2. METHOD

This research employs a qualitative approach with a case study design, as its primary objective is to explore in depth AI governance practices within managerial accounting systems, including how management control mechanisms are developed and implemented in real-world organizational contexts. The case study approach is particularly appropriate because it enables researchers to examine contextual processes, actors, and control dynamics, especially when the phenomenon under investigation is still evolving and cannot be separated from its organizational environment. The empirical focus is on companies located in the Batam industrial area, which provides a relevant setting characterized by efficiency pressures, supply chain integration, and a high demand for control systems. This approach facilitates a rich understanding of the “how” and “why” of AI governance practices, rather than testing causal relationships. Consequently, the qualitative case study method allows for a nuanced interpretation of accountability, decision-making discipline, and value creation as embedded in everyday organizational practices [13].

Data collection was conducted primarily through semi-structured interviews, as this format enables the exploration of participants’ experiences, considerations, and decision-making logic while maintaining consistency across key topics. The interviews addressed themes such as the use of AI in budgeting, cost control, and performance evaluation; the role of rules and control systems in shaping decisions; the distribution of decision-making authority; and organizational strategies for managing risks such as bias, overreliance, and lack of transparency. To enhance depth and credibility, interview data were supplemented with the analysis of relevant internal documents (e.g., budgeting SOPs, data access policies, performance dashboards, meeting minutes, and internal reports) and, where feasible, limited observations of control routines (e.g., budget meetings and performance review sessions). This multi-source approach enabled triangulation and reduced dependence on a single type of evidence, in line with qualitative research principles emphasizing contextual richness and convergence of evidence [13], [14].

The sampling technique employed purposive sampling, with participants selected based on their direct involvement in managerial accounting, management control, and exposure to AI or analytical systems within their organizational units. Priority was given to individuals occupying roles such as managerial accounting managers, finance managers, heads of operational units involved in budgeting and performance evaluation, and data/IT personnel responsible for developing or maintaining analytical systems. To broaden access to key informants, purposive sampling was complemented by snowball sampling, whereby initial participants recommended other relevant actors, particularly those holding decision-making authority or responsibilities related to AI governance. The number of participants was determined incrementally until data saturation was achieved, indicated by the absence of new substantive themes emerging from additional interviews. This role-based informant selection strategy is widely used in organizational research, where data quality depends more on the depth of experience than on the number of respondents.

To strengthen the transparency and validity of the data, the profile of informants is presented in an anonymized format in Table 1. The table outlines their positions, years of experience, and roles in relation to AI usage within their organizations.

Table 1. Anonymized Informant Profiles

Informant Code	Position	Years of Experience	Role in AI Usage and Governance
I1	Managerial Accounting Manager	12 years	Oversees AI-assisted budgeting and cost control systems
I2	Finance Manager	10 years	Uses AI for financial forecasting and performance review
I3	Operations Unit Head	8 years	Applies AI insights in operational decision-making
I4	Senior Controller	15 years	Designs control mechanisms integrating AI outputs

I5	Data Analyst / IT Specialist	7 years	Develops and maintains AI-based dashboards and models
I6	Performance Management Officer	9 years	Utilizes AI in KPI monitoring and evaluation processes

The data analysis technique employed thematic analysis through a systematic coding process, as it enables the extraction and interpretation of patterns related to AI governance and control mechanisms from qualitative data. The analysis followed several stages: data familiarization, initial coding, categorization of codes into themes, theme review, theme definition, and the development of a coherent thematic narrative aligned with the research objectives. The coding process was conducted iteratively, supported by analytical memos to maintain a clear audit trail, allowing interpretations to be traced back to empirical evidence. To enhance rigor, the study applied multiple validation strategies, including source triangulation (interviews, documents, and observations), limited member checking through validation of key findings summaries, and systematic documentation of analytical decisions throughout the coding process. This analytical approach is consistent with contemporary qualitative research standards that emphasize transparency, rigor, and the credibility of thematic interpretation [15], [16].

3. RESULT AND DISCUSSION

3.1 AI Governance Practices in Managerial Accounting in the Batam Industrial Estate

AI governance practices in managerial accounting within Batam's industrial estate demonstrate a predominantly instrumental and pragmatically embedded orientation, where AI is positioned as an advanced information-processing mechanism rather than an autonomous decision-making authority. In budgeting, AI enhances forecast accuracy and accelerates variance identification, effectively shifting managerial discussions from numerical reconciliation toward scenario evaluation and assumption testing. This transformation reflects a reconfiguration of control processes, in which AI facilitates faster cycles of organizational sensemaking but does not fundamentally replace managerial judgment. Similarly, in cost control, AI-enabled anomaly detection and cost intelligence dashboards introduce greater visibility into inefficiencies; however, their impact remains contingent upon their integration into formal control agendas. Without such integration, AI outputs risk remaining informational artefacts rather than actionable control instruments.

In performance evaluation, AI enables real-time and granular KPI monitoring, which strengthens diagnostic control capabilities but simultaneously introduces the risk of metric fixation. This condition echoes classical critiques of over-reliance on quantitative indicators, where performance metrics may obscure qualitative dimensions of organizational effectiveness. From the perspective of the Levers of Control Framework, this suggests an intensification of diagnostic control systems, while raising concerns about the relative underdevelopment of interactive control systems, which are essential for contextual interpretation and strategic dialogue.

The governance structure surrounding AI in Batam further reveals a cross-functional configuration involving controllers, financial managers, and IT/data teams. Controllers act as custodians of control logic defining KPIs, cost structures, and tolerance thresholds while data teams operationalize these parameters into analytical models. However, this division of roles generates tensions regarding authority boundaries, particularly when technical expertise is conflated with decision authority. In such cases, AI recommendations may be accepted with limited critical scrutiny, reinforcing a technocratic bias in decision-making processes.

Moreover, governance practices remain partially informal, as evidenced by norms such as treating AI outputs as advisory while preserving managerial discretion for final decisions. Although this aligns with the principle of "human-in-the-loop" control, it also creates ambiguity in accountability structures, especially in high-speed decision environments where AI outputs are perceived as objective and thus disproportionately influential. Consequently, AI governance in Batam has yet to achieve full institutionalization as a formalized control system; instead, it operates as an evolving socio-technical practice shaped by ongoing negotiation of roles, routines, and accountability mechanisms.

Critically, these findings resonate with broader literature emphasizing that digitalization transforms management control not merely through technological enhancement but through the reconfiguration of control routines and organizational practices. The observed reliance on AI as decision support aligns with global evidence that advanced analytics augment, rather than replace, managerial control functions. At the same time, the emergence of blurred accountability and over-reliance on algorithmic outputs reinforces concerns highlighted in prior studies regarding the dual effect of analytics systems: improving informational relevance while complicating responsibility attribution.

From a theoretical standpoint, the Batam case illustrates a hybridization of control modes. AI strengthens diagnostic controls through continuous monitoring and variance analysis, yet its effective use depends on the activation of interactive controls such as review meetings, assumption challenges, and cross-functional dialogue to interpret and contextualize outputs. This interplay underscores that AI does not diminish the need for managerial intervention; rather, it intensifies the importance of structured interaction, thereby transforming interactive control systems into more data-driven yet still socially mediated processes. Accordingly, the governance of AI must be understood not as a purely technical arrangement but as an extension of classical control principles into digitally mediated environments.

The finding that AI in Batam functions primarily as decision support, accelerating budgeting, cost control, and performance review, is consistent with the argument that digitalization transforms control practices primarily through shifts in control processes and routines, rather than simply increasing "technological sophistication" [5]. The cross-functional pattern between controllers and IT/data teams that shapes AI governance also aligns with the finding that digital data demands a reimagining of managerial accounting methods and practices so that analytical outputs become the basis for controlled actions [8]. However, the risk of blurred accountability and the tendency to over-reliance when system recommendations are perceived as objective reinforces evidence that enterprise systems and business analytics can simultaneously enhance the usefulness of information and increase the challenges of decision accountability [17]. Operationally, the need to "tame" AI output through review forums, clear indicator definitions, and assumption testing reflects the importance of strategic analytics project governance so that forecasting results are truly integrated into the control process, rather than remaining as additional information [7]. Thus, AI governance practices that still rely on informal rules and role negotiations emphasize the urgency of a control framework that maintains decision discipline and strategic renewal as emphasized in the management control literature [9], [10].

3.2 Management Control Mechanisms in Framing the Use of AI

To clarify how management control mechanisms frame the use of AI in everyday practice, the following Table summarizes the main governance themes found and their implications for managerial decision discipline and accountability.

Table 1. Management Control Mechanisms in Framing the Use of AI in Managerial Accounting

Control Theme	**Core Mechanism**	**Field Practice (Batam)**	**Implications for Decisions**
Decision rights & accountability	Decision owner andauthorization determination	AI provides recommendations; decisions are approved by the manager/controller (sign-off).	Clear accountability; reduces "blame AI."
AI use limits	Usage rules (allowed/disallowed)	AI output must be treated as support; final decisions must undergo human review.	Reduces overreliance; maintains decision discipline.
Data governance	Standardization of definitions & access control	Data dictionaries/KPIs are standardized; access is role-based; definition changes require approval.	Consistency of numbers; reduces interpretation conflicts.
Output validation	Reasonability testing & cross-verification	AI output is checked against historical/operational data before being used as the basis for budget/performance meetings.	Reduces wrong decisions due to noise/model drift.
Review & challenge routines	Control forum (budget/performance review)	AI output is discussed in meetings; assumptions and deviations are challenged; the controller facilitates.	More robust decisions; not just following the dashboard.
Transparency & bias	Explainability + bias checking	AI is asked to explain drivers; recommendations are evaluated for potential data/operational bias.	Healthier trust; reduced risk of bias and "blind trust."
Integration into control systems	Budget & KPI change procedures	Rolling updates are permitted, but must follow thresholds, documentation, and formal authorization.	Responsiveness without "budget chaos"; controls remain stable.

Control Theme	Core Mechanism	Field Practice (Batam)	Implications for Decisions
Decision trail	Documentation & audit trail	AI-based decisions are recorded: input, assumptions, approval, and managerial rationale.	Strengthens accountability and learning.
Change control	Change control model/dashboard	Model updates are not unilateral; there is impact testing and cross-functional approval.	Prevents decision shock; maintains control stability.
User capabilities	AI interpretation & limitations training	Training focuses on output interpretation, model limitations, and how to challenge them.	Improved judgment; reduced misinterpretation.

Source: Processed by Researchers, 2026

Beyond its descriptive richness, Table 1 provides a foundation for deeper theoretical interpretation when situated within classical management control frameworks. Each control theme can be mapped onto elements of the Levers of Control Framework, revealing how AI reshapes but does not replace established control mechanisms. First, themes such as *decision rights & accountability*, *AI use limits*, and *change control* correspond closely to boundary systems, which define acceptable domains of action. In the context of AI, these mechanisms prevent over-reliance on algorithmic outputs by explicitly requiring human authorization and formal approval processes. This reinforces the notion that AI governance must constrain as well as enable decision-making, ensuring that technological capabilities do not erode managerial responsibility. Second, *data governance*, *output validation*, and *integration into control systems* strengthen diagnostic control systems by improving data consistency, reliability, and comparability. AI amplifies the power of diagnostic controls through continuous monitoring and predictive analytics; however, the findings indicate that such enhancements also increase the risk of “false precision” if underlying assumptions are not critically examined. Thus, diagnostic sophistication must be complemented by mechanisms that ensure interpretive rigor. Third, *review & challenge routines* and *transparency & bias checking* reflect the evolution of interactive control systems in the digital era. Traditionally centered on face-to-face managerial dialogue, interactive controls are now increasingly mediated by AI-generated insights. Nevertheless, the Batam case demonstrates that these systems remain fundamentally social processes: AI outputs become meaningful only when subjected to discussion, challenge, and reinterpretation within control forums. In this sense, AI transforms interactive control systems into hybrid configurations that are both data-intensive and human-centric. Fourth, *decision trail* mechanisms align with principles of accountability and organizational learning, extending classical control concepts into the domain of digital traceability. By documenting inputs, assumptions, and managerial rationales, organizations create an auditable record that mitigates the opacity often associated with algorithmic decision-making. This is particularly important in addressing the “black box” problem, where the legitimacy of AI-supported decisions depends on their explainability. Finally, *user capabilities* highlight the enduring importance of human competence within technologically advanced control environments. Training focused on interpreting AI outputs and understanding model limitations reinforces the argument that effective control systems rely not only on technical infrastructure but also on cognitive and organizational capabilities. Taken together, these findings suggest that AI does not fundamentally disrupt classical management control theory; rather, it reconfigures its operationalization. The Batam case illustrates a shift toward more data-driven control systems that still depend critically on human judgment, interaction, and institutionalized accountability. Therefore, the challenge is not merely adopting AI technologies but embedding them within coherent control frameworks that balance automation with managerial oversight. This reinforces the broader theoretical insight that the effectiveness of AI in managerial accounting ultimately depends on how well it is aligned with, and governed by, established principles of management control.

This pattern aligns with the emphasis that digitalization demands a redesign of control practices to prevent data use from eroding decision-making discipline [5], [9]. However, when compared to the literature highlighting analytics and enterprise systems as drivers of increasingly automated decision-making in managerial accounting practices, these findings reveal a crucial difference: organizations are holding back AI from becoming a decision driver due to concerns about overreliance and blurred accountability [4]. A more subtle contradiction emerges at the implementation value level, as studies of analytics forecasting projects emphasize the need to integrate analytics output into control routines to generate predictive benefits, while the Batam findings indicate that such integration is often held back by authorization procedures and manual verification requirements that slow down the utilization of AI output [7]. In other words, compared to the narrative of "AI speeds up decisions", this finding is closer to the logic of "AI speeds up information, but decisions are still consciously slowed down" in order to maintain the stability of managerial control and accountability [8].

3.3 Implications of AI Governance on Accountability and Quality of Managerial Decisions

AI governance that frames the use of analytics as decision support has been shown to influence how managers interpret information more reflectively than reactively. Rather than accepting AI output as final truth, managers tend to treat it as a starting point for discussions to test assumptions, understand the operational context, and consider risk implications not captured by the model. This practice does slow decision-making compared to a fully automated approach, but it also improves the quality of judgment because information is processed through cross-functional dialogue and challenge. Thus, AI serves to enrich managerial sensemaking, rather than replace human judgment.

From an accountability perspective, AI governance that asserts decision ownership helps prevent the transfer of responsibility to the system when outcomes do not meet expectations. Clarity about who signs off on decisions and how AI recommendations are used creates clearer lines of accountability, although it also fosters defensiveness when decisions must be formally justified. In the context of value creation, AI is perceived as helpful when it increases cost visibility, accelerates problem identification, and supports more data-driven discussions, but is perceived as risky when it encourages overreliance or narrows the scope for interpretation. This implication emphasizes that the value of AI lies not in decision automation, but in its ability to strengthen accountability and decision quality through appropriate governance.

Your finding that AI in Batam is "used to enrich sensemaking but is deliberately limited to prevent it from becoming a decision driver" aligns with recent literature emphasizing that effective AI governance is built through the design of management controls, defining roles and responsibilities, control mechanisms, and evaluation dynamics, rather than simply adopting the technology [18]. Your emphasis on clarity of decision ownership and decision trails is also consistent with the notion that algorithmic accountability is an organizational practice that requires translating abstract ethical principles into operational governance instruments [19]. At the same time, your findings regarding the importance of explainability and more "reflective" discussions reinforce evidence that perceptions of transparency are closely related to a sense of accountability, trust, and acceptance of algorithmic decision systems [20]. Thus, your empirical contribution not only demonstrates that "AI helps," but also explains why AI's value emerges when organizations maintain human accountability and build challenge spaces that make AI outputs accountable.

4. CONCLUSION

This study concludes that AI governance in managerial accounting systems in emerging industrial regions does not primarily function as a decision-automating mechanism, but rather as a supporting tool that shapes discipline, accountability, and the quality of managerial judgment. The findings indicate that organizations consciously frame the use of AI through establishing decision rights, usage limits, and review and documentation routines, allowing analytical output to enrich the sensemaking process without shifting decision responsibility from humans to systems. This interpretation confirms that the study's objective of exploring the practices and meanings of AI governance in managerial accounting has been achieved, while also revealing that the value of AI arises more from the maturity of control mechanisms than from the sophistication of the technology itself.

The primary contribution of this study lies in providing contextual empirical evidence from emerging industrial regions that extends the managerial accounting literature by positioning AI governance as a negotiated organizational practice, rather than a mere issue of technology adoption. Based on these conclusions, this study recommends that practitioners and management clarify decision ownership, strengthen data governance, and instill a culture of challenging AI output to maintain accountability. Further research is recommended to explore the dynamics of AI governance across sectors or use longitudinal and comparative approaches to capture changes in practices over time. The limitations of this study lie in the focus of cases that are contextual and dependent on the interpretation of organizational actors, so that future studies need to expand the scope and triangulation of methods, and for policy makers it is recommended to formulate more operational AI governance guidelines for management control functions so that AI adoption in the industrial sector runs in a balance between efficiency, accountability, and value creation.

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