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AI-ASSISTED DECISION-MAKING AND ORGANIZATIONAL PERFORMANCE: AI-SUPPORTED MANAGEMENT ACCOUNTING INFORMATION IN THE DIGITAL SERVICES SMES

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Abstract

The integration of artificial intelligence (AI) into management accounting information systems represents a transformative shift in how small and medium-sized enterprises (SMEs) in the digital services sector make strategic decisions and enhance organizational performance. This research article synthesizes evidence from 30 empirical studies to examine the relationship between AI-assisted decision-making, management accounting information quality, and organizational performance outcomes in SMEs. Drawing on multiple theoretical frameworks including the Technology-Organization-Environment (TOE) Framework, Resource-Based View (RBV), and Information Processing Theory (IPT), this study reveals that AI-based accounting systems significantly enhance decision-making efficiency, cost information quality, and overall organizational performance. The methodology section synthesizes quantitative approaches predominantly employing structural equation modeling (SEM) and partial least squares (PLS-SEM) techniques across diverse SME contexts. Results demonstrate that AI adoption in management accounting systems explains up to 92.8% of variance in decision-making capacity, with significant positive effects on financial performance, operational efficiency, and strategic agility. Key findings indicate that AI-powered predictive analytics, automation capabilities, and real-time data processing enable SMEs to achieve improved cost accuracy, faster decision cycles, and enhanced competitive positioning. However, implementation challenges including high initial costs, data security concerns, and competency gaps remain significant barriers. This article contributes to the literature by providing a comprehensive synthesis of empirical evidence on AI's transformative role in management accounting for digital services SMEs, offering practical implications for managers, policymakers, and technology developers seeking to leverage AI for sustainable competitive advantage.

1. Introduction

The digital transformation of business operations has fundamentally altered how organizations collect, process, and utilize information for strategic decision-making. Small and medium-sized enterprises (SMEs), particularly those operating in digital services sectors, face increasing pressure to adopt advanced technologies to remain competitive in rapidly evolving markets. Artificial intelligence (AI) has emerged as a transformative force in management accounting, reshaping traditional practices and enabling unprecedented levels of analytical sophistication, automation, and predictive capability (Thongprim et al., 2025). The integration of AI into management accounting information systems represents not merely a technological upgrade but a fundamental reconceptualization of how financial and non-financial information supports organizational decision-making and performance.

Management accounting information systems serve as critical infrastructure for organizational decision-making, providing managers with timely, accurate, and relevant information for planning, controlling, and evaluating business operations. The quality of management accounting information directly influences decision-making efficiency, which in turn affects organizational performance outcomes including financial results, operational efficiency, and strategic positioning (Jesus et al., 2025). However, traditional management accounting systems often struggle with data volume, processing speed, and analytical complexity, particularly in dynamic digital services environments where real-time decision-making is essential for competitive advantage.

AI technologies, including machine learning, predictive analytics, natural language processing, and intelligent automation, offer solutions to these limitations by enhancing data processing capabilities, improving forecasting accuracy, automating routine tasks, and providing sophisticated analytical insights (Tenhunen, 2025). For SMEs in digital services sectors, AI adoption presents both significant opportunities and substantial challenges. While large enterprises may possess greater resources for AI implementation, SMEs can potentially achieve proportionally greater benefits due to their organizational agility and the transformative impact of AI on resource-constrained operations (Kwiotkowska, 2025).

Despite growing interest in AI applications for management accounting, the literature remains fragmented across multiple disciplines, theoretical perspectives, and empirical contexts. Existing research has examined AI adoption factors, technological capabilities, and performance outcomes, yet comprehensive synthesis of empirical evidence specifically addressing AI-assisted decision-making and management accounting information quality in digital services SMEs remains limited. This gap is particularly significant given the unique characteristics of SMEs, including resource constraints, organizational flexibility, and vulnerability to competitive pressures, which differentiate their AI adoption experiences from those of larger enterprises.

This research article addresses this gap by synthesizing empirical evidence from 30 studies examining AI-assisted decision-making, management accounting information systems, and organizational performance in SME contexts. The article is structured to provide comprehensive coverage of theoretical foundations, methodological approaches, empirical findings, and practical implications. Specifically, this study addresses three primary research questions: (1) How does AI integration in management accounting systems affect decision-making efficiency in digital services SMEs? (2) What are the mechanisms through which AI-supported management accounting information influences organizational performance? (3) What factors facilitate or inhibit successful AI implementation in SME management accounting contexts?

By synthesizing diverse empirical evidence through multiple theoretical lenses, this article contributes to both academic understanding and practical application of AI in management accounting for digital services SMEs. The findings provide actionable insights for SME managers considering AI adoption, policymakers developing support frameworks, and technology developers designing AI solutions tailored to SME needs and constraints.

2. Literature Review and Theoretical Foundations

2.1 AI in Management Accounting: Conceptual Overview

Artificial intelligence in management accounting encompasses a range of technologies and applications designed to enhance the collection, processing, analysis, and presentation of financial and non-financial information for managerial decision-making. AI-based accounting systems integrate machine learning algorithms, predictive analytics, natural language processing, and automation capabilities to transform traditional accounting practices (Priyanka, 2025). These systems enable real-time data processing, pattern recognition, anomaly detection, and predictive modeling that extend far beyond the capabilities of conventional accounting information systems.

The evolution of AI in accounting reflects broader trends in digital transformation, moving from simple automation of routine tasks to sophisticated analytical capabilities that support strategic decision-making. Early applications focused on automating data entry, transaction processing, and basic reporting functions. Contemporary AI systems, however, provide advanced capabilities including predictive cash flow modeling, intelligent cost allocation, automated variance analysis, and real-time performance dashboards (Tenhunen, 2025). For digital services SMEs, these capabilities are particularly valuable given the fast-paced, data-intensive nature of their operating environments.

AI-driven management accounting systems offer several distinct advantages over traditional approaches. First, they dramatically reduce manual processing time, with studies reporting reductions of up to 80% in routine accounting tasks (Tenhunen, 2025). Second, they enhance accuracy and reliability by minimizing human error and applying consistent analytical frameworks across large datasets. Third, they enable real-time or near-real-time information availability, supporting agile decision-making in dynamic business environments. Fourth, they provide sophisticated analytical capabilities including scenario modeling, predictive forecasting, and pattern recognition that would be impractical or impossible with manual methods (Haridasan et al., 2024).

2.2 Theoretical Frameworks

Research on AI adoption and impact in management accounting draws on multiple theoretical frameworks, each offering distinct perspectives on the phenomenon. The Technology-Organization-Environment (TOE) Framework provides a comprehensive lens for understanding AI adoption decisions, considering technological characteristics (compatibility, complexity, relative advantage), organizational factors (top management support, organizational resources, business strategy), and environmental influences (competitive pressure, market structure, regulatory environment) (Thongprim et al., 2025), (Wong et al., 2024). This framework is particularly relevant for SMEs, where adoption decisions are influenced by resource constraints and environmental pressures.

The Resource-Based View (RBV) positions AI capabilities and management accounting information systems as strategic resources that can provide sustainable competitive advantage when they are valuable, rare, inimitable, and non-substitutable (Liang, 2025), (Mensah et al., 2025). From this perspective, AI-enhanced management accounting systems represent organizational capabilities that enable superior decision-making and performance outcomes. The RBV framework emphasizes the importance of complementary resources, including human capital, organizational processes, and data infrastructure, in realizing the potential value of AI investments.

Information Processing Theory (IPT) provides theoretical grounding for understanding how AI enhances organizational decision-making by improving information processing capabilities (Liang, 2025), (Nassani et al., 2023), (Pham et al., 2022). According to IPT, organizations face information processing requirements determined by environmental uncertainty and task complexity. AI systems enhance organizational information processing capacity by enabling faster data collection, more sophisticated analysis, and more effective information distribution. This theoretical perspective is particularly relevant for understanding how AI-supported management accounting information improves decision-making efficiency.

Decision Usefulness Theory (DUT) focuses on the quality characteristics of accounting information that make it useful for decision-making, including relevance, reliability, timeliness, and understandability (Thongprim et al., 2025). AI systems can enhance these quality characteristics by providing more timely information, improving accuracy through automated error detection, and presenting information in more accessible formats through visualization and natural language interfaces. This framework emphasizes the mediating role of information quality in linking AI adoption to decision-making and performance outcomes.

Innovation Diffusion Theory (IDT) explains how AI technologies spread through organizational populations, identifying factors that influence adoption rates including relative advantage, compatibility, complexity, trialability, and observability (Thongprim et al., 2025), (Wong et al., 2024). For SMEs, perceived complexity and compatibility with existing systems are particularly important adoption barriers, while relative advantage in terms of cost savings and performance improvements serves as a key driver.

2.3 AI and Decision-Making in SMEs

Decision-making in SMEs differs from that in large enterprises in several important respects. SME decision-making is typically more centralized, with owners or small management teams making most strategic and operational decisions. This centralization can enable faster decision-making but also creates information bottlenecks and increases the importance of decision support tools (Dhanekula et al., 2023). SMEs often lack specialized analytical staff, making automated AI-driven insights particularly valuable. Additionally, SMEs face greater resource constraints, making decision-making efficiency and accuracy critical for survival and growth.

AI enhances SME decision-making through multiple mechanisms. Predictive analytics enable forward-looking decision support, allowing managers to anticipate market trends, customer behavior, and operational challenges (Scaria et al., 2025). Machine learning algorithms can identify patterns and relationships in data that would be difficult or impossible for human analysts to detect, particularly in large or complex datasets (Domínguez et al., 2020). Natural language processing enables extraction of insights from unstructured data sources including customer feedback, market reports, and industry news (Tenhunen, 2025). Automation of routine analytical tasks frees managerial time and attention for higher-value strategic thinking.

Empirical evidence demonstrates significant positive effects of AI on decision-making capabilities in SMEs. Studies report that AI adoption explains substantial variance in decision-making capacity, with some research finding that AI accounts for over 90% of variance in decision-making efficiency measures (Haridasan et al., 2024). AI-enhanced management information systems show positive correlations with decision outcomes, decision speed, and cross-functional alignment (Dhanekula et al., 2023). These effects are particularly pronounced in contexts requiring rapid response to changing conditions, complex data analysis, or integration of multiple information sources.

2.4 Management Accounting Information Quality

The quality of management accounting information is a critical determinant of decision-making effectiveness and organizational performance. Information quality encompasses multiple dimensions including accuracy, timeliness, completeness, relevance, and reliability. AI systems can enhance each of these dimensions through different mechanisms. Accuracy improves through automated error detection, consistent application of accounting rules, and elimination of manual data entry errors. Timeliness improves through real-time or near-real-time data processing and automated reporting. Completeness improves through integration of diverse data sources and comprehensive data capture. Relevance improves through intelligent filtering and presentation of information tailored to specific decision contexts.

Cost information quality represents a particularly important dimension of management accounting information for SMEs, where cost management is often critical for profitability and survival. AI-based systems

enhance cost information quality through automated cost allocation, real-time cost tracking, predictive cost modeling, and intelligent variance analysis (Thongprim et al., 2025). These capabilities enable more accurate product costing, better cost control, and more informed pricing decisions. Research demonstrates that cost information quality serves as a mediating variable linking AI adoption to decision-making efficiency and organizational performance.

The relationship between AI adoption and information quality is not automatic but depends on implementation quality, data infrastructure, and organizational capabilities. Successful AI implementation requires high-quality input data, appropriate system configuration, and effective integration with existing information systems (Nassani et al., 2023). Organizations must also develop capabilities to interpret and act on AI-generated insights, suggesting that human capital development is a critical complement to technological investment.

2.5 Organizational Performance Outcomes

Organizational performance in SMEs encompasses multiple dimensions including financial performance (profitability, revenue growth, return on assets), operational performance (efficiency, productivity, quality), and strategic performance (market position, innovation, adaptability). AI-supported management accounting information can influence each of these performance dimensions through improved decision-making, enhanced operational efficiency, and better strategic positioning.

Financial performance improvements from AI adoption occur through multiple pathways. Enhanced cost information enables better cost control and more profitable pricing decisions. Improved cash flow forecasting supports better working capital management and reduces financing costs. Automated financial processes reduce administrative costs and free resources for value-adding activities (Kawadkar, 2026). Empirical evidence demonstrates significant positive associations between AI adoption and financial performance indicators, with some studies reporting that AI adoption shows the strongest association with financial performance among various performance dimensions.

Operational performance improvements result from process automation, enhanced efficiency, and better resource allocation. AI systems can optimize production scheduling, inventory management, and resource deployment based on predictive models and real-time data (Scaria et al., 2025). Automation of routine tasks reduces processing time and error rates while enabling staff to focus on higher-value activities. Studies report operational efficiency improvements including reduced manual processing time, improved reporting accuracy, and enhanced continuous monitoring capabilities (Tenhunen, 2025).

Strategic performance improvements emerge from enhanced strategic decision-making, improved market responsiveness, and better competitive positioning. AI-enabled scenario modeling supports strategic planning by allowing managers to evaluate multiple strategic options and their likely outcomes. Real-time market intelligence enables faster response to competitive threats and market opportunities. Enhanced analytical capabilities support innovation by identifying new market opportunities and customer needs (Kwiotkowska, 2025). Research demonstrates that AI capability, when combined with appropriate digital strategy and organizational maturity, leads to superior organizational performance through complex synergistic interactions.

3. Methodology

This section synthesizes the methodological approaches employed in existing empirical research examining AI-assisted decision-making, management accounting information systems, and organizational performance in SME contexts. The synthesis draws on 30 studies that provide empirical evidence on these relationships, documenting research designs, data collection methods, analytical techniques, and theoretical frameworks applied across diverse geographical and sectoral contexts.

3.1 Research Design Approaches in Existing Literature

The predominant research design in the reviewed literature is quantitative, with the

majority of studies employing survey-based cross-sectional designs to examine relationships between AI adoption, management accounting information quality, decision-making efficiency, and organizational performance. Quantitative approaches enable statistical testing of hypothesized relationships and measurement of effect sizes, providing empirical evidence for theoretical propositions (Haridasan et al., 2024), (Liang, 2025), (Nassani et al., 2023).

Several studies employed mixed-methods designs combining qualitative and quantitative approaches to provide richer insights into AI adoption and impact. For example, Thongprim et al. (2025) combined in-depth interviews with 15 SME accounting managers with a quantitative survey of 372 SMEs, allowing qualitative insights into implementation experiences to complement quantitative measurement of relationships and effects. Similarly, Pham et al. (2022) employed literature review, expert interviews, and survey methods to develop and test a model of digitalization in accounting information systems.

A smaller number of studies employed purely qualitative approaches, including systematic literature reviews and case study analyses. Rainy et al. (2023) conducted a systematic review synthesizing 175 peer-reviewed articles, industry white papers, and empirical case studies to evaluate AI-driven decision support capabilities. Tenhunen (2025) employed a mixed-methods approach combining critical literature synthesis with multiple global case studies to illustrate benefits and challenges of AI integration in management accounting.

One methodologically innovative study employed fuzzy-set qualitative comparative analysis (fsQCA), a configurational approach that examines complex synergistic interactions among multiple conditions (Kwiotkowska, 2025). This approach is particularly valuable for understanding how combinations of AI capability, digital strategy, and digital maturity lead to high organizational performance, recognizing that multiple pathways may lead to similar outcomes.

3.2 Data Collection Methods

Survey questionnaires represent the primary data collection method in the reviewed literature, with studies employing both online and paper-based instruments. Sample sizes varied considerably, ranging from 56 SMEs in the fsQCA study (Kwiotkowska, 2025) to 583 respondents in a study of Vietnamese SMEs (Pham et al., 2022). Most studies achieved sample sizes between 200 and 400 respondents, providing adequate statistical power for structural equation modeling and regression analyses.

Sampling approaches included random sampling, purposive sampling, and convenience sampling, with most studies targeting specific populations such as SME owners, accounting managers, finance professionals, or chief accountants. For example, Haridasan et al. (2024) collected data from 479 SME owners or representatives in manufacturing who had used AI, while Mensah et al. (2025) surveyed 204 small-scale enterprises in Cape Coast, Ghana. Geographic contexts varied widely, including studies from Thailand (Thongprim et al., 2025), China (Liang, 2025), Vietnam (Van et al., 2024), (Pham et al., 2022), Ghana (Mensah et al., 2025), Malaysia (Wong et al., 2024), Pakistan (Nassani et al., 2023), Indonesia (Ardiansah et al., 2021), and Germany (Ulrich et al., 2021).

Measurement instruments typically employed multi-item scales based on established constructs from prior research, with most studies using five-point or seven-point Likert scales. Constructs measured included AI adoption or capability, accounting information system characteristics, information quality dimensions, decision-making efficiency, and various organizational performance indicators. Several studies developed new measurement instruments tailored to their specific research contexts while drawing on established theoretical frameworks.

Qualitative data collection employed semi-structured interviews with key informants including SME owners, accounting managers, and finance professionals. Interview samples were typically smaller, ranging from 15 to 30 participants, with interviews exploring implementation experiences, perceived benefits and challenges, and organizational impacts of AI adoption (Thongprim et al., 2025), (Pham et al., 2022).

3.3 Analytical Techniques

Structural Equation Modeling (SEM) represents the most frequently employed analytical technique in the reviewed literature, used to test complex models involving multiple constructs, direct effects, indirect effects, and mediating relationships. Studies employed both covariance-based SEM using AMOS software (Thongprim et al., 2025), (Pham et al., 2022), (Ardiansah et al., 2021) and variance-based Partial Least Squares SEM (PLS-SEM) (Liang, 2025), (Van et al., 2024), (Wong et al., 2024), (Mensah et al., 2025). PLS-SEM is particularly appropriate for exploratory research and complex models with many constructs, while covariance-based SEM is preferred when strong theoretical foundations exist and model fit assessment is important.

SEM analyses typically included measurement model assessment (confirmatory factor analysis, reliability and validity testing) followed by structural model assessment (path coefficients, significance testing, variance explained). Reliability was assessed using Cronbach's alpha and composite reliability, with most studies reporting values above 0.70 indicating acceptable reliability. Validity was assessed through convergent validity (average variance extracted) and discriminant validity (Fornell-Larcker criterion, heterotrait-monotrait ratio).

Regression analysis was employed in several studies to examine relationships between AI adoption and performance outcomes. For example, Kawadkar (2026) used regression models to assess relationships between AI adoption and financial, operational, and strategic performance dimensions. Mensah et al. (2025) employed multiple regression to identify significant predictors of performance among various AI perception dimensions. Dhanekula et al. (2023) used correlation and regression analysis to examine relationships among AI-enhanced MIS capability, usage intensity, and decision outcomes.

Descriptive statistics were employed across studies to characterize samples and variables, including means, standard deviations, frequencies, and percentages. Several studies employed t-tests to compare groups or test hypotheses about population parameters (Mensah et al., 2025). Factor analysis was used to identify underlying dimensions in multi-item scales and reduce data complexity (Haridasan et al., 2024).

The fsQCA approach employed by Kwiotkowska (2025) represents a distinct analytical paradigm, examining necessary and sufficient conditions for high organizational performance through set-theoretic methods. This approach identifies multiple configurations of conditions that lead to the outcome of interest, recognizing equifinality (multiple paths to the same outcome) and causal complexity.

3.4 Theoretical Frameworks Applied

The reviewed studies employed diverse theoretical frameworks to ground their research and interpret findings. The Technology-Organization-Environment (TOE) Framework was among the most frequently applied, used to structure understanding of AI adoption factors across technological, organizational, and environmental dimensions (Thongprim et al., 2025), (Wong et al., 2024). The TOE framework provides comprehensive coverage of adoption determinants and is particularly well-suited to SME contexts where organizational and environmental factors often constrain technological choices.

The Resource-Based View (RBV) was applied to position AI capabilities and accounting information systems as strategic resources that can provide competitive advantage (Thongprim et al., 2025), (Liang, 2025), (Mensah et al., 2025). RBV emphasizes the importance of developing valuable, rare, inimitable, and non-substitutable capabilities, suggesting that successful AI implementation requires not just technology adoption but development of complementary organizational capabilities.

Information Processing Theory (IPT) provided theoretical grounding for understanding how AI enhances organizational information processing capabilities and decision-making (Liang, 2025), (Nassani et al., 2023), (Pham et al., 2022). IPT focuses on the match between information processing requirements (determined by uncertainty and complexity) and information processing capacity (determined by systems and structures), with AI systems enhancing organizational capacity.

Decision Usefulness Theory (DUT) and Innovation Diffusion Theory (IDT) were integrated with other frameworks in several

studies (Thongprim et al., 2025). DUT emphasizes information quality characteristics that support decision-making, while IDT explains technology diffusion patterns based on innovation characteristics and adopter perceptions.

Additional theoretical perspectives included Dynamic Capabilities Framework, emphasizing firms' ability to reconfigure competencies in response to change (Tenhunen, 2025), Socio-technical Systems Theory, considering interdependence between human actors and technological systems (Tenhunen, 2025), Stakeholder Theory, addressing multiple stakeholder interests in accounting information (Pham et al., 2022), and Technology Acceptance Model (TAM), focusing on perceived usefulness and ease of use as adoption determinants (Mensah et al., 2025).

Several studies employed multiple theoretical frameworks in integrated models, recognizing that no single theory fully captures the complexity of AI adoption and impact in organizational contexts. For example, Thongprim et al. (2025) integrated TOE Framework, IDT, DUT, and RBV to provide comprehensive theoretical grounding for their study of AI-based accounting systems in Thai SMEs.

4. Results

This section synthesizes empirical findings from the reviewed literature, organizing results around five key themes: AI impact on decision-making efficiency, effects on management accounting information quality, organizational performance outcomes, mediating and moderating factors, and implementation challenges and success factors.

4.1 AI Impact on Decision-Making Efficiency

Empirical evidence consistently demonstrates significant positive effects of AI adoption on decision-making efficiency in SME contexts. The most striking finding comes from Haridasan et al. (2024), who reported that AI explains 92.8% of variance in decision-making capacity (R^2 = 0.928, β = 0.963, t = 78.141, $p < 0.001$) among manufacturing SMEs. This exceptionally high explanatory power suggests that AI capability is a dominant determinant of decision-making capacity in organizations that have adopted AI technologies.

Thongprim et al. (2025) found that AI-based accounting systems significantly positively affect decision-making efficiency in Thai SMEs, with this effect operating both directly and indirectly through cost information quality. The study demonstrated that SMEs with higher levels of AI adoption achieve improved cost accuracy, faster decision cycles, and stronger managerial confidence. Qualitative interviews revealed that AI integration enhances data accuracy, automates repetitive accounting processes, and accelerates reporting timelines, all of which contribute to more efficient decision-making.

Dhanekula et al. (2023) reported that AI-enhanced MIS capability shows strong positive correlations with decision outcomes ($r = 0.68$, $p < 0.001$) and significantly affects decision outcomes ($\beta = 0.41$, $p < 0.001$) in a sample of 352 SMEs across multiple sectors. The study found particularly positive effects on decision speed and cross-functional alignment, suggesting that AI enhances not only the quality of individual decisions but also the efficiency of organizational decision processes.

Mensah et al. (2025) found that AI integration significantly improved decision-making in small-scale enterprises in Ghana ($p < 0.001$), with AI perceptions explaining 48% of performance variance. The study identified specific AI characteristics that predict enhanced decision-making, including cost reduction capabilities, accuracy improvements, task simplification, and wider adoption facilitation.

The mechanisms through which AI enhances decision-making efficiency include automation of routine analytical tasks, provision of real-time or near-real-time information, sophisticated predictive analytics, pattern recognition in complex data, and intelligent presentation of information tailored to decision contexts. Tenhunen (2025) reported that machine learning reduces manual processing time by up to 80%, freeing managerial attention for higher-value strategic thinking. The study also found that AI implementation reduced manual accounting time by 44% and improved reporting accuracy by 20% in leading firms.

4.2 AI Effects on Management Accounting Information Quality

AI adoption significantly enhances multiple dimensions of management accounting information quality, with particularly strong effects on accuracy, timeliness, and cost information quality. Thongprim et al. (2025) demonstrated that AI-based accounting systems significantly positively affect cost information quality, which in turn exhibits a strong mediating effect linking technology adoption to decision-making efficiency and organizational performance. This finding highlights the critical role of information quality as a mechanism through which AI influences organizational outcomes.

Mensah et al. (2025) found that AI improving accuracy and reliability was one of the strongest predictors of enhanced performance ($\beta = +0.29$, $p < 0.001$) in Ghanaian small-scale enterprises. Similarly, AI encouraging wider AIS adoption ($\beta = +0.30$, $p = 0.001$) significantly predicted performance improvements, suggesting that information quality improvements from AI adoption have cascading effects on organizational outcomes.

Pham et al. (2022) reported that digitalization of accounting information significantly affected quality of information on financial reports ($\beta = 0.519$, $p < 0.001$) in Vietnamese SMEs. The study demonstrated that information quality plays an important role in sustainable innovation ecosystem generation ($\beta = 0.677$, $p < 0.001$) and positively affects public value creation ($\beta = 0.492$, $p < 0.001$), indicating that information quality improvements have broad organizational and societal impacts.

Van et al. (2024) found that cloud-based AIS usage significantly contributes to AIS effectiveness, which encompasses information quality dimensions including accuracy, timeliness, completeness, and relevance. The study demonstrated that AIS effectiveness positively influences organizational performance, with firm size moderating the relationship between cloud-based AIS usage and AIS effectiveness.

Specific information quality improvements documented in the literature include enhanced data accuracy through automated error detection and elimination of manual data entry errors, improved timeliness through real-time or near-real-time data processing and automated reporting, better completeness through integration of diverse data sources and comprehensive data capture, and increased relevance through intelligent filtering and context-specific information presentation (Priyanka, 2025), (Scaria et al., 2025).

4.3 Organizational Performance Outcomes

Empirical evidence demonstrates significant positive effects of AI adoption on multiple dimensions of organizational performance in SME contexts. Financial performance improvements are particularly well-documented, with several studies reporting strong associations between AI adoption and financial outcomes.

Kawadkar (2026) found that AI adoption significantly and positively influences organizational performance across financial, operational, and strategic dimensions, with financial performance showing the strongest association. The study surveyed 370 accounting and finance professionals and found that AI enhances cost control, process optimization, and data-driven decision-making, leading to measurable financial improvements.

Mensah et al. (2025) reported that AI integration significantly improved sales growth and profitability in Ghanaian small-scale enterprises ($p < 0.001$). The study found that AI perceptions explained 48% of performance variance, with specific AI characteristics including cost reduction, accuracy improvement, and task simplification serving as significant predictors of enhanced performance.

Liang (2025) demonstrated that AI adoption significantly positively affects firm performance in Chinese mid-sized and large enterprises, with accounting information systems exhibiting a partial mediating effect. This finding suggests that AI improves performance through internalization via information systems, enabling a shift from experience-based to data-driven strategic decision-making.

Operational performance improvements are also well-documented. Haridasan et al. (2024) found that AI explains 86.8% of variance in automation of accounting systems ($R^2 = 0.868$, $\beta = 0.932$, $t = 56.002$, $p < 0.001$), indicating that AI dramatically enhances operational efficiency in accounting processes. The study reported that AI helps executives make smarter decisions,

improves financial services quality, and enhances competitiveness, leading to better organizational performance.

Tenhunen (2025) reported multiple operational improvements from AI implementation, including 44% reduction in manual accounting time, 20% improvement in reporting accuracy, 50% enhancement in continuous auditing, 40% improvement in fraud detection, and 25% increase in forecasting accuracy. These improvements translate directly into operational efficiency gains and cost savings.

Strategic performance improvements emerge from enhanced strategic decision-making capabilities and improved competitive positioning. Kwiotkowska (2025) found that high organizational performance in SMEs results from complex synergistic interactions among digital strategy, digital maturity, and AI capability, with AI technical resources being mandatory for any viable high-performance configuration. This finding suggests that AI capability is a necessary but not sufficient condition for superior performance, requiring complementary strategic and organizational capabilities.

Dhanekula et al. (2023) reported that AI-enhanced MIS platforms improve strategic decision outcomes, particularly decision speed and cross-functional alignment. The study found that usage intensity partially mediates the relationship between AI-MIS capability and decision outcomes ($\beta = 0.47$, $p < 0.001$), suggesting that realizing AI benefits requires active utilization of AI capabilities in decision processes.

4.4 Mediating and Moderating Factors

The relationship between AI adoption and organizational performance is not direct but operates through multiple mediating and moderating mechanisms. Cost information quality emerges as a critical mediating variable in several studies. Thongprim et al. (2025) demonstrated that cost information quality exhibits a strong mediating effect, linking AI-based accounting systems and financial reporting quality to decision-making efficiency and organizational performance. This finding suggests that AI influences performance not directly but by enhancing the quality of information available for decision-making.

Accounting information system effectiveness serves as another important mediating mechanism. Liang (2025) found that AIS exhibited a partial mediating effect in the relationship between AI adoption and firm performance, indicating that AI improves performance through internalization via information systems. Similarly, Van et al. (2024) demonstrated that cloud-based AIS usage influences organizational performance indirectly through AIS effectiveness, enhancing profitability and supporting sustainability activities.

Usage intensity mediates the relationship between AI capability and decision outcomes. Dhanekula et al. (2023) found that usage intensity partially mediates the capability-outcomes relationship ($\beta = 0.47$, $p < 0.001$), suggesting that organizations must actively utilize AI capabilities to realize performance benefits. This finding highlights the importance of organizational practices and user engagement in translating technological capabilities into performance outcomes.

Firm size emerges as an important moderating variable. Van et al. (2024) found that firm size moderates the relationship between cloud-based AIS usage and AIS effectiveness, suggesting that the benefits of AI adoption may vary depending on organizational scale. This finding has important implications for understanding differential AI impacts across the SME spectrum from micro to medium-sized enterprises.

Digital maturity and digital strategy serve as contextual factors that shape AI impact on performance. Kwiotkowska (2025) demonstrated that high organizational performance results from complex synergistic interactions among AI capability, digital strategy, and digital maturity, with multiple equifinal configurations leading to high performance. This finding suggests that AI capability must be aligned with broader digital transformation initiatives to maximize performance impact.

Knowledge management practices and balanced scorecard implementation may also mediate the AI-performance relationship, though empirical evidence on these mechanisms is more limited. The literature suggests that AI effectiveness depends on complementary organizational capabilities including data infrastructure,

analytical skills, and change management capacity.

4.5 Implementation Challenges and Success Factors

Despite significant potential benefits, AI implementation in SME management accounting faces multiple challenges. High initial investment costs represent a primary barrier, particularly for resource-constrained SMEs. Scaria et al. (2025) noted that although AI implementation presents challenges including high initial investment costs and data security concerns, long-term benefits significantly outweigh these obstacles.

Competency gaps and skill shortages constitute another major challenge. Ulrich et al. (2021) found that lack of competence was identified as a significant barrier by 65% of German SME respondents. This finding highlights the importance of human capital development as a complement to technological investment. Organizations must develop capabilities to implement, operate, and interpret AI systems, requiring training, recruitment, or external partnerships.

Data quality and infrastructure limitations can constrain AI effectiveness. AI systems require high-quality input data to generate reliable insights, yet many SMEs lack robust data management practices and integrated information systems. Data silos, inconsistent data formats, and incomplete data capture can limit AI system effectiveness (Rainy et al., 2023).

Security and privacy concerns represent important adoption barriers, particularly for SMEs handling sensitive financial information. Wong et al. (2024) identified security and privacy as factors influencing AI adoption decisions in Malaysian MSMEs. Organizations must balance the benefits of AI-enabled data analysis with the risks of data breaches and privacy violations.

Organizational resistance to change can impede AI implementation. The literature notes that cultural issues related to resistance to change are often underemphasized relative to technical aspects of AI implementation. Successful AI adoption requires not only technological deployment but also organizational change management, stakeholder engagement, and cultural adaptation.

Success factors for AI implementation include strong top management support, which facilitates resource allocation, organizational commitment, and change management. Wong et al. (2024) found that top management support positively influences AI adoption in MSMEs. Alignment with business strategy ensures that AI investments support organizational objectives and priorities. Wong et al. (2024) found that business strategy support positively influences AI adoption decisions.

Adequate organizational resources, including financial capital, human capital, and technological infrastructure, enable successful AI implementation. Wong et al. (2024) found that organizational resources positively influence AI adoption in Malaysian MSMEs. Compatibility with existing systems and processes facilitates integration and reduces implementation complexity. Wong et al. (2024) found that compatibility positively influences AI adoption intentions.

External pressures including competitive pressure and government regulations can drive AI adoption. Wong et al. (2024) found that competitive pressure and government regulations positively influence AI adoption in MSMEs. These external factors can overcome internal resistance and resource constraints by creating compelling business cases for AI investment.

5. Discussion

5.1 Theoretical Implications

The synthesized empirical evidence provides strong support for multiple theoretical perspectives on AI adoption and impact in management accounting contexts. The consistently significant positive effects of AI on decision-making efficiency, information quality, and organizational performance support the Resource-Based View's proposition that AI capabilities constitute strategic resources that can provide competitive advantage (Liang, 2025), (Mensah et al., 2025). The finding that AI explains up to 92.8% of variance in decision-making capacity (Haridasan et al., 2024) suggests that AI capability may be among the most powerful determinants of decision-making effectiveness in contemporary organizational contexts.

Information Processing Theory receives strong empirical support from findings demonstrating that AI enhances organizational information processing capabilities, leading to improved decision-making and performance (Liang, 2025), (Nassani et al., 2023), (Pham et al., 2022). The mediating role of information quality in linking AI adoption to performance outcomes (Thongprim et al., 2025) aligns with IPT's emphasis on information processing capacity as a determinant of organizational effectiveness. These findings suggest that AI systems enhance organizational capacity to collect, process, analyze, and distribute information, enabling more effective responses to environmental uncertainty and task complexity.

The Technology-Organization-Environment Framework's comprehensive perspective on adoption determinants receives support from findings identifying technological factors (compatibility, complexity), organizational factors (top management support, resources, strategy), and environmental factors (competitive pressure, regulations) as significant influences on AI adoption (Wong et al., 2024). These findings confirm that AI adoption decisions in SMEs are shaped by multiple contextual factors beyond purely technological considerations.

The finding that high organizational performance results from complex synergistic interactions among AI capability, digital strategy, and digital maturity (Kwiotkowska, 2025) extends theoretical understanding by highlighting configurational complexity and equifinality. This suggests that simple linear models may inadequately capture the complexity of AI impact on performance, and that multiple pathways involving different combinations of capabilities and strategies can lead to superior outcomes. This finding aligns with configurational theories emphasizing that organizational outcomes result from complex interactions among multiple factors rather than simple additive effects.

The mediating role of cost information quality (Thongprim et al., 2025) and AIS effectiveness (Liang, 2025), (Van et al., 2024) in linking AI adoption to performance outcomes provides empirical support for Decision Usefulness Theory's emphasis on information quality characteristics as determinants of decision-making effectiveness. These findings suggest that AI influences performance not directly but through enhancement of information quality, which in turn supports better decision-making. This theoretical insight has important implications for understanding the mechanisms through which AI creates organizational value.

The literature also reveals theoretical gaps and opportunities for further development. The relative underemphasis on cultural and behavioral factors compared to technical factors suggests that socio-technical perspectives deserve greater attention in future research. The limited attention to long-term organizational resilience effects of AI adoption indicates a need for longitudinal theoretical frameworks. The predominant focus on large enterprises in some theoretical development suggests that SME-specific theories of AI adoption and impact warrant further elaboration.

5.2 Practical Implications for Digital Services SMEs

The empirical evidence provides several important practical implications for SME managers considering AI adoption in management accounting contexts. First, the consistently strong positive effects of AI on decision-making efficiency, information quality, and organizational performance suggest that AI investment can generate substantial returns for SMEs, despite implementation challenges and costs. The finding that AI explains 92.8% of variance in decision-making capacity (Haridasan et al., 2024) indicates that AI adoption can fundamentally transform decision-making capabilities, potentially providing significant competitive advantage.

Second, the mediating role of information quality suggests that SMEs should focus not only on AI technology adoption but also on ensuring that AI systems enhance information quality dimensions including accuracy, timeliness, completeness, and relevance. This implies that successful AI implementation requires attention to data quality, system integration, and information presentation, not just algorithm sophistication. SMEs should invest in data infrastructure and data management practices as complements to AI technology adoption.

Third, the importance of usage intensity as a mediating factor (Dhanekula et al., 2023)

suggests that realizing AI benefits requires active utilization of AI capabilities in decision processes. SMEs should focus on user training, change management, and organizational practices that encourage AI system utilization. Technology adoption alone is insufficient; organizations must develop practices and routines that embed AI insights into decision-making processes.

Fourth, the finding that high performance results from synergistic interactions among AI capability, digital strategy, and digital maturity (Kwiotkowska, 2025) suggests that AI adoption should be integrated with broader digital transformation initiatives. SMEs should develop coherent digital strategies that align AI investments with organizational objectives, capabilities, and market positioning. Isolated AI implementations without strategic alignment and organizational readiness may fail to generate expected benefits.

Fifth, the identification of multiple implementation challenges including high costs, competency gaps, data quality issues, and security concerns (Scaria et al., 2025), (Ulrich et al., 2021) suggests that SMEs should carefully assess their readiness for AI adoption and develop comprehensive implementation plans addressing these challenges. This may include phased implementation approaches, partnerships with technology providers, investment in training and skill development, and attention to data governance and security.

Sixth, the success factors identified in the literature including top management support, business strategy alignment, adequate resources, and system compatibility (Wong et al., 2024) provide a roadmap for successful AI implementation. SMEs should ensure that these success factors are in place before committing to major AI investments. Top management should champion AI initiatives, allocate adequate resources, align AI investments with business strategy, and ensure compatibility with existing systems and processes.

For digital services SMEs specifically, the real-time information processing capabilities and predictive analytics offered by AI systems are particularly valuable given the fast-paced, data-intensive nature of digital services environments. The ability to process large volumes of transaction data, identify patterns in customer behavior, predict market trends, and optimize resource allocation in real-time can provide significant competitive advantage in digital services markets. SMEs in this sector should prioritize AI capabilities that support rapid decision-making and market responsiveness.

5.3 Integration of AI and Management Accounting Systems

The successful integration of AI with management accounting systems requires attention to multiple technical, organizational, and human factors. Technically, integration requires robust data infrastructure including data warehouses or lakes that consolidate data from multiple sources, application programming interfaces (APIs) that enable data exchange between systems, and data quality management processes that ensure accuracy, completeness, and consistency (Nassani et al., 2023).

AI systems must be configured to address specific management accounting needs including cost allocation and analysis, budgeting and forecasting, performance measurement and reporting, variance analysis, and profitability analysis. Generic AI solutions may require customization to address industry-specific or organization-specific accounting requirements. SMEs should work with technology providers to ensure that AI systems are appropriately configured for their specific contexts.

Integration also requires attention to information presentation and user interfaces. AI-generated insights must be presented in formats that are accessible and actionable for managers who may lack technical expertise in AI or data science. Visualization tools, natural language interfaces, and automated reporting can make AI insights more accessible to non-technical users (Tenhunen, 2025). SMEs should prioritize AI solutions that provide intuitive interfaces and clear presentation of insights.

Organizationally, integration requires changes to roles, responsibilities, and processes. Accountants' roles may shift from data entry and routine processing to analysis, interpretation, and advisory functions (Priyanka, 2025). Organizations must redefine job descriptions, develop new competencies, and redesign workflows to leverage AI capabilities effectively.

This organizational transformation requires change management, training, and stakeholder engagement.

Human factors are critical for successful integration. Users must trust AI systems and understand their capabilities and limitations. Organizations should provide training on AI system operation, interpretation of AI-generated insights, and appropriate use of AI in decision-making. Transparency about AI algorithms and decision logic can build user trust and facilitate appropriate reliance on AI recommendations.

5.4 Limitations and Challenges

Despite the substantial benefits documented in the literature, AI adoption in SME management accounting faces multiple limitations and challenges that warrant careful consideration. The high initial investment costs represent a significant barrier for resource-constrained SMEs, potentially limiting AI adoption to larger or more profitable SMEs (Scaria et al., 2025). This raises concerns about a potential digital divide where smaller or less profitable SMEs are unable to access AI benefits, potentially widening performance gaps within the SME sector.

Competency gaps and skill shortages constitute a fundamental challenge that may limit AI effectiveness even when technology is adopted (Ulrich et al., 2021). Many SMEs lack staff with expertise in AI, data science, or advanced analytics, making it difficult to implement, operate, and interpret AI systems effectively. This challenge is compounded by competition for AI talent from larger enterprises that can offer higher compensation and more attractive career opportunities. SMEs may need to rely on external partnerships, consultants, or cloud-based AI services that provide managed solutions.

Data quality and availability limitations can constrain AI effectiveness. AI systems require large volumes of high-quality data to train algorithms and generate reliable insights, yet many SMEs lack comprehensive historical data or have data quality issues including incompleteness, inconsistency, and inaccuracy. These data limitations may reduce AI system effectiveness or require substantial data cleaning and preparation efforts before AI implementation.

Algorithmic bias and ethical challenges represent emerging concerns that are currently under-researched in the SME context. AI algorithms can perpetuate or amplify biases present in training data, potentially leading to discriminatory outcomes in areas such as credit decisions, pricing, or resource allocation. SMEs may lack the expertise to identify and mitigate algorithmic bias, raising ethical and legal concerns. Greater attention to algorithmic transparency, fairness, and accountability is needed in future research and practice.

Security and privacy risks associated with AI systems require careful management. AI systems often require access to sensitive financial and operational data, creating potential vulnerabilities to data breaches or unauthorized access. Cloud-based AI services raise additional concerns about data sovereignty and third-party access to sensitive information. SMEs must implement robust security measures and carefully evaluate the security practices of AI service providers.

The long-term organizational resilience effects of AI adoption remain poorly understood.

While short-term performance benefits are well-documented, the long-term implications for organizational capabilities, employment, and sustainability are less clear. Excessive reliance on AI systems could potentially reduce human expertise and judgment capabilities, creating vulnerabilities if AI systems fail or prove inadequate in novel situations. Organizations should maintain human oversight and develop complementary human capabilities alongside AI adoption.

The literature reveals a predominant focus on technical aspects of AI implementation at the expense of cultural and behavioral factors. Resistance to change, organizational culture, and human-AI collaboration dynamics receive less attention than algorithm design and system architecture. This imbalance suggests that socio-technical perspectives emphasizing the interdependence of human and technological factors deserve greater attention in future research and practice.

Finally, the lack of sector-specific models and frameworks represents a limitation in current understanding. AI adoption and impact may vary significantly across industries due to

differences in business models, competitive dynamics, regulatory environments, and technological requirements. The digital services sector may have distinct characteristics that shape AI adoption and effectiveness, yet sector-specific research remains limited. Future research should develop more nuanced understanding of how industry context shapes AI adoption and impact.

6. Conclusion and Future Directions

6.1 Summary of Key Findings

This research article has synthesized empirical evidence from 30 studies examining AI-assisted decision-making, management accounting information systems, and organizational performance in SME contexts. The synthesis reveals several key findings that advance understanding of AI's transformative role in management accounting for digital services SMEs.

First, AI adoption significantly enhances decision-making efficiency in SMEs, with empirical evidence demonstrating that AI explains up to 92.8% of variance in decision-making capacity (Haridasan et al., 2024). This exceptionally strong effect suggests that AI capability is a dominant determinant of decision-making effectiveness in organizations that have adopted AI technologies. The mechanisms through which AI enhances decision-making include automation of routine analytical tasks, provision of real-time information, sophisticated predictive analytics, pattern recognition in complex data, and intelligent information presentation.

Second, AI significantly improves management accounting information quality across multiple dimensions including accuracy, timeliness, completeness, and relevance. Cost information quality emerges as a particularly important mediating variable linking AI adoption to decision-making efficiency and organizational performance (Thongprim et al., 2025). This finding highlights that AI influences performance not directly but through enhancement of information quality, which in turn supports better decision-making.

Third, AI adoption leads to significant improvements in organizational performance across financial, operational, and strategic dimensions. Financial performance improvements include enhanced profitability, revenue growth, and cost control. Operational improvements include reduced processing time, improved accuracy, and enhanced efficiency. Strategic improvements include better market responsiveness, enhanced competitive positioning, and improved strategic decision-making capabilities (Kawadkar, 2026), (Mensah et al., 2025), (Tenhunen, 2025).

Fourth, the relationship between AI adoption and organizational performance operates through multiple mediating mechanisms including information quality, AIS effectiveness, and usage intensity. High organizational performance results from complex synergistic interactions among AI capability, digital strategy, and digital maturity, with multiple equifinal configurations leading to superior outcomes (Kwiotkowska, 2025). This finding suggests that AI capability must be aligned with broader organizational capabilities and strategies to maximize performance impact.

Fifth, AI implementation faces multiple challenges including high initial costs, competency gaps, data quality limitations, security concerns, and organizational resistance to change. Success factors include top management support, business strategy alignment, adequate resources, system compatibility, and external pressures including competitive pressure and regulatory requirements (Wong et al., 2024), (Scaria et al., 2025), (Ulrich et al., 2021).

6.2 Recommendations for Practice

Based on the synthesized evidence, several recommendations emerge for SME managers, policymakers, and technology developers seeking to leverage AI for enhanced management accounting and organizational performance.

For SME managers, the evidence strongly supports strategic investment in AI capabilities for management accounting, given the substantial performance benefits documented across multiple studies. However, successful implementation requires comprehensive planning addressing technical, organizational, and human factors. Managers should assess organizational readiness including data infrastructure, staff capabilities, and change management capacity before committing to

major AI investments. Phased implementation approaches may be appropriate, starting with specific high-value applications and expanding as capabilities and experience develop.

Managers should prioritize information quality as a critical success factor, investing in data infrastructure, data governance, and data quality management as complements to AI technology adoption. AI systems require high-quality input data to generate reliable insights, making data management a foundational capability for AI effectiveness. Integration of AI with existing management accounting systems requires careful attention to technical compatibility, process redesign, and user training.

Managers should develop organizational capabilities to utilize AI insights effectively in decision-making processes. Technology adoption alone is insufficient; organizations must develop practices and routines that embed AI insights into decision processes, supported by training, change management, and performance management systems that encourage AI utilization. Human oversight and judgment remain critical complements to AI capabilities, particularly for strategic decisions involving uncertainty, ambiguity, or ethical considerations.

For policymakers, the evidence suggests that AI adoption can enhance SME competitiveness and performance, supporting economic development objectives. However, implementation barriers including high costs, competency gaps, and data infrastructure limitations may prevent many SMEs from accessing AI benefits. Policy interventions could address these barriers through financial support programs, training and education initiatives, data infrastructure development, and regulatory frameworks that encourage responsible AI adoption while protecting against risks.

Policymakers should consider developing sector-specific support programs recognizing that AI adoption challenges and opportunities may vary across industries. For digital services SMEs specifically, policies supporting data infrastructure, digital skills development, and technology adoption could enhance sector competitiveness. International cooperation on AI standards, data governance, and ethical frameworks could facilitate cross-border AI adoption and reduce compliance burdens for SMEs operating in multiple markets.

For technology developers, the evidence highlights the importance of developing AI solutions tailored to SME needs and constraints. SME-appropriate solutions should be affordable, easy to implement and operate, compatible with existing systems, and provide clear value propositions. Cloud-based AI services offering managed solutions may be particularly appropriate for SMEs lacking internal AI expertise. User interfaces should be intuitive and accessible to non-technical users, with clear presentation of insights and recommendations.

Technology developers should prioritize data security, privacy protection, and algorithmic transparency to address SME concerns and build trust in AI systems. Configurable solutions that can be customized to specific industry or organizational contexts may provide greater value than generic one-size-fits-all approaches. Partnerships with accounting software providers, industry associations, and SME support organizations could facilitate AI adoption by embedding AI capabilities in familiar platforms and providing trusted implementation support.

6.3 Future Research Directions

While the synthesized evidence provides substantial insights into AI's role in management accounting for SMEs, several important research gaps and opportunities for future investigation emerge from this review.

First, longitudinal research examining the long-term effects of AI adoption on organizational performance, capabilities, and resilience is needed. Most existing studies employ cross-sectional designs that capture short-term effects but cannot address questions about sustainability of performance improvements, evolution of AI capabilities over time, or long-term organizational adaptation to AI-enabled decision-making. Longitudinal studies tracking SMEs over multiple years could provide insights into the dynamics of AI adoption, learning effects, and long-term performance trajectories.

Second, research examining the mechanisms through which AI influences organizational performance in greater depth would enhance theoretical understanding. While mediating roles of information quality and AIS

effectiveness are documented, the specific processes through which AI-generated insights are translated into decisions and actions warrant closer examination. Process-oriented research employing qualitative methods such as ethnography or process tracing could illuminate the micro-level mechanisms linking AI capabilities to organizational outcomes.

Third, comparative research examining AI adoption and impact across different industry sectors, organizational sizes, and national contexts would enhance understanding of contextual factors shaping AI effectiveness. The digital services sector may have distinct characteristics that differentiate AI adoption and impact from manufacturing, retail, or professional services sectors. Similarly, micro, small, and medium-sized enterprises may face different challenges and opportunities. Cross-national research could identify how institutional, cultural, and regulatory contexts shape AI adoption patterns and outcomes.

Fourth, research addressing ethical, social, and sustainability implications of AI adoption in SME management accounting is needed. Current research emphasizes performance benefits while giving less attention to potential negative consequences including employment effects, algorithmic bias, privacy concerns, and environmental impacts of AI systems. Critical perspectives examining power dynamics, equity implications, and sustainability considerations would provide more balanced understanding of AI's societal implications.

Fifth, research examining human-AI collaboration and the changing role of management accountants in AI-enabled organizations would provide practical insights for workforce development and organizational design. How do management accountants' roles, skills, and identities evolve as AI systems assume routine analytical tasks? What new competencies are required for effective human-AI collaboration? How do organizations redesign workflows and decision processes to leverage both human and AI capabilities effectively?

Sixth, research developing and testing sector-specific models and frameworks for AI adoption and impact in digital services SMEs would enhance practical relevance. Generic frameworks may inadequately capture the specific characteristics, challenges, and opportunities of digital services contexts. Sector-specific research could identify critical success factors, implementation approaches, and performance metrics tailored to digital services SME contexts.

Seventh, research examining the role of AI in supporting sustainability and social responsibility objectives in SME management accounting would address an important emerging concern. How can AI systems support environmental accounting, social impact measurement, and integrated reporting? What are the opportunities and challenges for using AI to enhance SME sustainability performance? How do AI-enabled management accounting systems support stakeholder engagement and accountability?

Finally, methodological innovation employing configurational approaches, machine learning methods, and mixed-methods designs could enhance understanding of the complex, context-dependent nature of AI adoption and impact. The finding that high performance results from complex synergistic interactions among multiple factors (Kwiotkowska, 2025) suggests that configurational approaches such as fsQCA may be particularly valuable for understanding equifinality and causal complexity. Machine learning methods could be applied to identify patterns in large-scale datasets on AI adoption and performance. Mixed-methods designs combining quantitative measurement of effects with qualitative exploration of mechanisms and contexts could provide richer insights than either approach alone.

In conclusion, AI represents a transformative technology for management accounting in digital services SMEs, offering substantial potential for enhanced decision-making efficiency, information quality, and organizational performance. However, realizing this potential requires careful attention to implementation challenges, organizational capabilities, and contextual factors. Future research addressing the gaps and opportunities identified in this review will enhance both theoretical understanding and practical application of AI in management accounting for SMEs.

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