International Conference on Sustainable Economics, Management, and Accounting (ICSEMA 2026)
Proceedings
Vol. 02 Year 2026, 2229 – 2240
ISSN: 3109-3337

AI INTEGRATION IN ENTERPRISE RESOURCE PLANNING FOR FINANCIAL RESILIENCE AND SUSTAINABILITY OF ORGANIZATIONS

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Article Information: Received --- June, 25 2026, Published --- August, 10 2026

Abstract

Amid global economic uncertainty driven by geopolitical conflicts and multidimensional crises, organizations are required to take strategic and adaptive measures to enhance their resilience and ensure operational sustainability. One of the key strategies is the implementation of Enterprise Resource Planning (ERP) systems, further strengthened through integration with Artificial Intelligence (AI). The integration of AI into ERP systems offers a proactive solution for managing cash flow, detecting financial anomalies at an early stage, and optimizing working capital. However, empirical evidence on the effectiveness of AI–ERP integration in developing countries remains limited. This study employs a literature review approach to synthesize existing research on AI–ERP integration across major ERP vendors, including SAP, Oracle, and Odoo, with the aim of providing strategic insights to enhance organizational resilience in the face of global crises. The findings indicate that AI-enhanced ERP systems are capable of forecasting cash flow, identifying irregular transactions, accelerating financial closing processes, and generating automated financial reports. These capabilities contribute significantly to improving financial resilience. Nevertheless, several challenges persist, particularly in terms of data quality and the availability of skilled human resources. Recommended strategies include phased implementation, maintaining human oversight in decision-making processes, and conducting thorough data cleansing prior to AI deployment. Furthermore, research on AI-ERP integration in Indonesia remains scarce, with most existing studies focusing solely on ERP adoption without AI integration. Therefore, substantial research opportunities remain open, particularly in strengthening organizational resilience in developing economies such as Indonesia through AI-ERP adoption.

Keywords: Artificial Intelligence, Enterprise Resource Planning (ERP), Financial Sustainability, Financial Resilience

INTRODUCTION

The digital era has fundamentally transformed how organizations operate. Globalization, market volatility, and increasingly stringent regulatory pressures compel firms to continuously enhance operational efficiency while maintaining financial resilience. Stakeholders including investors, regulators, shareholders, and society at large no longer demand profitability alone but also expect transparency, accountability, and resilience in financial management. In this context,

the concept of financial sustainability has become increasingly critical, particularly amid uncertainties such as rising interest rates, inflation, and geopolitical conflicts (Darlia et al., 2026; Duan et al., 2019). Financial sustainability extends beyond mere survival; it reflects an organization's ability to sustain growth through sound cash flow management, optimal working capital utilization, and strategic resilience against economic shocks.

For decades, Enterprise Resource Planning (ERP) systems have served as the technological backbone of organizational operations. ERP integrates core business functions such as finance, human resources, supply chain, manufacturing, and distribution into a centralized database, enabling real-time information flow across departments (Winasis et al., 2025). Through ERP implementation, organizations can eliminate data silos, reduce redundancy, and improve reporting accuracy. However, in the post-pandemic era of accelerated digital transformation and increasing business complexity, traditional ERP systems have begun to reveal significant limitations. These systems are not designed to process large volumes of data at high speed, nor to provide adaptive decision support in rapidly changing environments (Aktürk, 2021). Conventional ERP systems are largely reactive, recording historical transactions rather than anticipating future conditions or recommending strategic actions.

To address these limitations, Artificial Intelligence (AI) has emerged as a transformative catalyst for ERP systems. Recent studies indicate that integrating AI technologies including machine learning (ML), deep learning (DL), natural language processing (NLP), predictive and prescriptive analytics, and generative AI-into ERP systems unlocks capabilities that extend far beyond rule-based automation. This integration transforms ERP from a transactional system into an intelligent decision-support platform capable of forecasting cash flows, automating financial reconciliation, optimizing working capital, detecting anomalous transactions, and generating decision recommendations autonomously (Duan et al., 2019; Parimi, 2024). For example, ML enables ERP systems to learn from customer payment patterns and predict receivables inflows; NLP facilitates automated invoice processing and journal entries; and generative AI can produce narrative financial reports (Dmitri, 2024).

Despite the substantial potential of AI–ERP integration, comprehensive literature examining its specific impact on financial sustainability remains limited and fragmented. Existing studies predominantly focus on operational efficiency improvements such as reduced processing time and cost savings while offering limited insights into how AI–ERP contributes to financial resilience, liquidity management, and sustainable financial governance (Mannan et al., 2025; Srbinoska & Donovska, 2023). In other words, a gap persists between rapidly advancing technological capabilities and systematic academic understanding of how AI–ERP concretely supports financial sustainability in modern organizations. While several studies report accelerated financial closing processes enabled by AI, few explicitly measure how such improvements translate into enhanced liquidity or reduced reliance on short-term financing (Sharma, 2025).

There is a clear urgency to conduct a systematic and comprehensive literature review on AI–ERP integration in supporting financial sustainability. This urgency is driven by three key factors. First, the rapid adoption of cloud-based ERP and generative AI technologies in industry has outpaced academic research, creating a knowledge gap between practice and theory. Major ERP vendors such as SAP, Oracle, and Odoo have introduced AI-enabled features, yet independent academic evaluations of their effectiveness remain scarce (Gartner, 2025; SAP, 2025; Oracle, 2025; Odoo, 2025). Second, increasing regulatory pressure related to financial governance, risk management, and transparency necessitates evidence-based frameworks for implementation. Regulators across jurisdictions are beginning to question how AI-driven decisions can be audited and held accountable (Ranasinghe & Gide, 2025; Deloitte, 2026). Third, organizational decision-makers including Chief Financial Officers (CFOs), Chief Information Officers (CIOs), and other strategic stakeholders require structured and validated guidance for designing effective AI–ERP investment strategies to achieve long-term financial resilience (McKinsey, 2026). Without such

guidance, organizations risk investing heavily in technologies that fail to deliver expected value (Raza, 2025).

Beyond these global gaps, there is also a significant contextual gap in Indonesia. Research on AI integration within ERP systems in Indonesia remains scarce and underexplored (Sipayung, 2025). Existing studies largely focus on ERP adoption without incorporating AI. For instance, Winasis and Dinariyana (2025) demonstrate that ERP implementation enhances startup sustainability by improving process structure and transparency, thereby increasing survival rates. However, such studies do not address AI integration. Emerging research on AI–ERP integration in Indonesia is still limited to early-stage investigations in specific industries, such as AI-based forecasting and ERP flexibility in inventory optimization (Sipayung, 2025). Moreover, awareness and adoption of AI among Indonesian firms remain relatively low, indicating that many organizations have yet to fully leverage AI capabilities within their ERP systems (Wu, 2025). This situation presents substantial opportunities for academics and practitioners to explore and develop best practices for AI–ERP integration in Indonesia's unique business environment, characterized by the dominance of SMEs, cultural diversity, and digital infrastructure challenges.

Based on the above background, this literature review is designed to address three primary research questions. First, how is AI integrated into ERP systems to support financial functions that contribute to organizational financial sustainability? Second, what empirical evidence exists regarding the impact of AI–ERP implementation on financial sustainability metrics? Third, what are the key challenges, risks, and implementation strategies in adopting AI–ERP for financial sustainability, particularly in relation to contemporary business conditions, including implementations by major vendors such as SAP, Oracle, and Odoo? This study aims to map patterns of AI–ERP integration in financial functions, synthesize evidence on its impact on financial sustainability metrics, and identify relevant challenges, risks, and implementation strategies. The scope of this review covers publications from 2020 to 2026, focusing on studies that simultaneously address AI and ERP integration from technical, managerial, and policy perspectives in both English and Indonesian contexts. Accordingly, this literature review is expected to provide theoretical contributions by synthesizing fragmented literature and practical contributions by offering evidence-based guidance for CFOs, financial managers, ERP vendors, and regulators.

LITERATURE REVIEW AND HYPOTHESIS FORMULATION

To understand the integration of Artificial Intelligence (AI) into Enterprise Resource Planning (ERP) systems in supporting financial sustainability, this study adopts three primary theoretical lenses: the Technology–Organization–Environment (TOE) framework, the Resource-Based View (RBV), and Upper Echelons Theory. These frameworks provide complementary perspectives for analyzing technology adoption, strategic resource utilization, and managerial decision-making, as highlighted in prior studies (Aktürk, 2021; Antonova et al., 2024; Morawiec et al., 2023).

The Technology–Organization–Environment (TOE) framework, originally developed by Tornatzky and Fleischer (1990), remains one of the most widely used models for explaining technology adoption. According to this framework, adoption decisions are influenced by three contexts: technological, organizational, and environmental. In the context of AI–ERP integration, the technological dimension includes the maturity of AI technologies (e.g., machine learning, deep learning, natural language processing, and generative AI), compatibility with existing ERP systems, technical complexity, and data security considerations (Antonova et al., 2024). The organizational dimension encompasses top management support, financial human resource readiness, innovation culture, IT budget availability, and firm size (Kurup & Gupta, 2022). Meanwhile, the environmental dimension involves competitive pressure, regulatory requirements (e.g., financial governance regulations), vendor ecosystem support (such as SAP, Oracle, and Odoo), and macroeconomic conditions including interest rates and inflation (McKinsey, 2026). The TOE framework is

particularly relevant as AI–ERP adoption extends beyond purely technical considerations and is shaped by complex organizational and environmental dynamics (Pinto et al., 2025).

The Resource-Based View (RBV), popularized by Barney (1991), posits that sustainable competitive advantage arises from resources that are valuable, rare, inimitable, and organizationally embedded (VRIO). In this context, integrating AI into ERP systems creates new strategic resources, including high-quality integrated data across business functions, real-time predictive capabilities that are difficult for competitors to replicate without similar infrastructure, and enhanced organizational adaptability through continuously learning machine learning models (Barney & Hesterly, 2019). The Dynamic Capabilities Theory (Teece, 2007) extends RBV by emphasizing the organization's ability to integrate, build, and reconfigure resources in response to changing environments (Nwankpa & Roumani, 2025). Embedding AI into ERP systems enables the development of three key dynamic capabilities: sensing, seizing, and transforming. Sensing allows organizations to detect financial risks and opportunities early through anomaly detection (Middae et al., 2024); seizing enables rapid exploitation of opportunities through AI-driven prescriptive analytics, such as dynamic discounting strategies (Mannan et al., 2025); and transforming supports continuous process improvement through self-learning models, such as adaptive cash flow forecasting (Singh, 2025).

Upper Echelons Theory (Hambrick & Mason, 1984) suggests that organizational outcomes are partially predicted by the characteristics, values, and experiences of top executives, particularly CEOs and CFOs. In the context of AI–ERP adoption for financial sustainability, managerial cognition and leadership orientation play a critical role. CFOs with strong technological literacy are more likely to adopt AI-driven financial forecasting, whereas more conservative leaders may prefer maintaining human-in-the-loop decision structures (Caridi et al., 2026). This theory also explains variations in AI investment priorities across organizations, with some focusing on cash flow forecasting and others on fraud detection, depending on leadership risk perception and prior experience (Raza, 2025; Kurup & Gupta, 2022).

ERP systems themselves have undergone significant evolution over the past three decades. According to Aktürk (2021), ERP development can be categorized into four generations. The first generation (ERP I, 1990s–2000) focused on on-premise systems integrating core internal modules such as materials management, sales, finance, and control, but was characterized by high costs and limited flexibility. The second generation (ERP II, 2000–2015) introduced e-business capabilities, customer relationship management (CRM), and supply chain management (SCM), along with web-based access, although analytics remained largely historical (Martins & Marques, 2025). The third generation (Cloud ERP, 2015–2022) enabled multi-tenant architectures, real-time accessibility, and automatic updates (Alsharari, 2022). The fourth generation (AI-embedded Cloud ERP, 2023–present) incorporates AI/ML, predictive analytics, NLP, and generative AI assistants, although maturity levels vary across vendors (Gartner, 2025). Leading ERP vendors—including SAP, Oracle, and Odoo—have entered this fourth generation with differing levels of AI integration readiness (SAP, 2025; Oracle, 2025; Odoo, 2025).

Cloud-native architecture serves as a critical enabler of AI integration due to its ability to provide real-time access to data from both internal ERP modules and external sources (e.g., banking systems and market data), scalable computational power, continuous model updates, and compliance with financial data security regulations (Deloitte, 2026). A comparison of major cloud ERP platforms reveals distinct approaches to AI integration. SAP S/4HANA Cloud leverages in-memory databases optimized for real-time analytics and offers embedded AI through assistants such as Joule (SAP, 2025). Oracle Fusion Cloud ERP employs a multi-tenant architecture with automated databases and integrated AI, including agentic AI capable of autonomous operations (Oracle, 2025; Cherukuri & Yarram, 2024). Odoo, in both Community and Enterprise editions, utilizes relational databases with extensions and provides flexible open-source development tools, although AI integration often relies on APIs (Odoo, 2025). In terms of SME suitability, SAP is generally positioned for large enterprises, Oracle targets mid-to-large organizations (with NetSuite

for SMEs), while Odoo offers a cost-effective solution particularly suitable for SMEs and startups (Wu, 2025).

Artificial Intelligence (AI) is broadly defined as the capability of computer systems to perform tasks that typically require human intelligence, including learning, reasoning, perception, and language understanding (Duan et al., 2019). Several AI techniques are particularly relevant to ERP and financial functions. Machine Learning (ML) enables systems to learn from historical data and generate predictions, such as cash flow forecasting (Singh, 2025). Deep Learning (DL) enhances predictive accuracy by capturing complex patterns, including individual customer payment behavior. Natural Language Processing (NLP) and generative AI enable systems to interpret and generate human language, supporting automated financial reporting (Dmitri, 2024; Blankespoor et al., 2026). Agentic AI refers to autonomous systems capable of making and executing decisions, for instance in bank reconciliation processes (Joshi, 2025). Anomaly detection techniques identify unusual patterns in financial data, supporting fraud detection and risk management (Umeorah et al., 2024).

Recent studies indicate that AI adoption in corporate finance is evolving from rule-based automation toward cognitive automation capable of understanding, predicting, and recommending actions (Parimi, 2024; Faccia & Petratos, 2024). Key application areas include cash flow forecasting incorporating external economic indicators such as interest rates and inflation (Singh, 2025), automated financial closing processes (Oracle, 2025), and working capital optimization through dynamic discounting based on real-time financial insights (Mannan et al., 2025).

In this study, financial sustainability is operationally defined as an organization's ability to maintain healthy cash flows, adequate liquidity, and stable profitability in the short to medium term, without excessive reliance on uncertain external financing, while remaining resilient to external shocks such as economic downturns or liquidity crises (Fernaldy & Deniswara, 2025; Iansiti & Lakhani, 2020). This definition differs from traditional financial performance metrics by emphasizing resilience and agility under uncertainty (Schrage et al., 2023). Based on the literature, key financial metrics influenced by AI–ERP integration include cash flow forecast accuracy, receivables collection speed, payables management, cash conversion cycle, financial closing speed, and fraud detection rates. Empirical studies consistently report significant improvements in these metrics following AI–ERP implementation (Gu, 2024; Mannan et al., 2025; SAP, 2025).

RESEARCH METHODS

This study adopts a qualitative approach using a narrative literature review to synthesize existing knowledge on the integration of Artificial Intelligence (AI) and Enterprise Resource Planning (ERP) systems in supporting financial sustainability.

The literature search was conducted across multiple academic databases, including Google Scholar, Scopus, and other reputable sources, covering publications from 2020 to 2026. The search strategy employed a combination of keywords such as "AI ERP financial sustainability," "cash flow forecasting AI," "SAP AI finance," "Oracle AI ERP," "Odoo AI," and "AI–ERP integration in Indonesia."

Inclusion criteria were defined to ensure the relevance and quality of selected studies. Specifically, the review included articles, reports, and conference papers that (1) explicitly discuss the integration of AI and ERP systems, (2) address aspects of financial sustainability or financial performance related to resilience, and (3) were published within the last decade. Studies that focused solely on ERP without AI integration or lacked relevance to financial outcomes were excluded.

Following the screening process, approximately 40–50 relevant sources were selected for in-depth analysis. The data were analyzed using a thematic analysis approach, whereby findings were categorized into four main themes: (1) patterns of AI–ERP integration, (2) impacts on financial sustainability, (3) implementation challenges and risks, and (4) recommended strategies and best practices.

To enhance the validity and reliability of the findings, source triangulation was applied by comparing evidence across multiple studies, along with cross-verification of original publications to ensure consistency and accuracy. The research was conducted over a one-month period using virtual access to digital databases.

RESULTS AND DISCUSSION

Across the reviewed studies, qualitative case studies emerged as the most dominant research design, followed by experimental or simulation-based studies and systematic literature reviews. SAP appears as the most frequently examined ERP vendor, followed by Oracle and Odoo. In terms of industry coverage, manufacturing dominates, followed by retail, distribution, and financial services. Most studies focus on large enterprises, while small and medium-sized enterprises (SMEs) remain underrepresented. These findings indicate that although AI–ERP adoption is expanding across sectors and regions, a significant research gap persists in SMEs and developing countries, including Indonesia (Sipayung, 2025; Winasis & Dinariyana, 2025).

Patterns of AI–ERP Integration in Financial Functions

Thematic analysis identifies four primary architectural patterns of AI–ERP integration. The first pattern is embedded AI, where AI capabilities are natively integrated within ERP systems, as seen in SAP Joule, Oracle Fusion AI, and Odoo AI agents. This approach offers advantages such as lower integration costs, optimized performance, enhanced security, and strong vendor support. However, it also introduces limitations, including vendor lock-in, limited model customization, and relatively higher licensing costs (Antonova et al., 2024). This model is predominantly adopted by SAP and Oracle users (SAP, 2025; Oracle, 2025).

The second pattern is the add-on AI layer via API, where AI models are developed externally (e.g., using Python, R, or TensorFlow) and integrated into ERP systems through APIs. This approach provides high flexibility, supports open-source tools, and reduces vendor dependency. However, it requires substantial technical expertise, increases system complexity, and introduces potential API security risks (Wu, 2025; Odoo, 2025). This pattern is commonly found in Odoo ecosystems and organizations with strong internal technical capabilities (Machinser Group, 2025).

The third pattern is the hybrid edge–cloud architecture, in which lightweight AI models operate at the edge for real-time responsiveness, while more complex models are trained in the cloud. This architecture enables fast response times, reduces network dependency, and supports offline functionality. However, it introduces challenges in model synchronization and distributed system management (Giantsidi & Tarantola, 2025; Iansiti & Lakhani, 2020).

The fourth pattern involves conversational AI assistants (co-pilot/generative AI) integrated into ERP interfaces. These systems leverage large language models to enable natural language interaction, automate narrative financial reporting, and improve user accessibility. Despite these advantages, risks such as hallucination, data security concerns, and limited maturity for critical financial decision-making remain significant (Ranasinghe & Gide, 2025; Blankespoor et al., 2026; Dmitri, 2024).

Across financial functions, five domains show the highest adoption of AI within ERP systems. Cash flow forecasting is the most prominent application due to its critical role in financial sustainability, often utilizing techniques such as LSTM, ARIMA, and hybrid models (Singh, 2025; Giantsidi & Tarantola, 2025). Anomaly and fraud detection ranks second, driven by the need for real-time monitoring, with unsupervised learning methods such as Isolation Forest widely used (Middae et al., 2024; Umeorah et al., 2024). Financial closing and reconciliation processes benefit from NLP-based automation, including invoice processing through OCR (Oracle, 2025; Odonkor et al., 2024). Working capital optimization employs reinforcement learning and prescriptive analytics to improve receivables and payables management (Mannan et al., 2025). Finally, financial reporting

increasingly utilizes generative AI to produce narrative reports that enhance managerial decision-making (Dmitri, 2024; Blankespoor et al., 2026).

From a vendor perspective, integration capabilities vary. SAP, with its embedded AI approach, demonstrates strengths in cash flow forecasting, anomaly detection, and receivables/payables automation (SAP, 2025). Oracle, leveraging embedded AI and intelligent agents, excels in financial closing, intercompany reconciliation, and narrative reporting (Oracle, 2025). Odoo, with its flexible add-on architecture, is particularly strong in invoice OCR, anomaly detection, and basic forecasting, especially due to its compatibility with Python-based machine learning libraries (Odoo, 2025).

Impact on Financial Sustainability

Most studies reporting quantitative evidence indicate that AI–ERP implementation significantly improves key financial sustainability metrics. Cash flow forecasting accuracy improves substantially compared to traditional statistical or manual methods (Singh, 2025; Fernaldy & Deniswara, 2025). The time required for monthly financial closing is significantly reduced, enabling faster access to financial information and more timely decision-making (Oracle, 2025; Raza, 2025). Fraud detection capabilities are enhanced, reducing financial losses associated with irregular transactions (Middae et al., 2024).

In addition, organizations demonstrate improved efficiency in managing receivables and payables, leading to shorter cash conversion cycles and stronger liquidity positions (Mannan et al., 2025; Gu, 2024). Several industry reports also highlight improved return on investment (ROI) for organizations that successfully implement AI–ERP solutions (Raza, 2025; Oracle, 2025).

Concrete case evidence further illustrates these benefits. For example, the implementation of SAP S/4HANA in BMW's manufacturing operations enabled the integration of financial and logistics data across global plants, improving data consistency and enabling duplicate invoice detection (SAP, 2025). Similarly, studies in the Indonesian SME retail sector indicate that AI–ERP adoption significantly enhances cash flow forecasting accuracy, reducing reliance on short-term bank financing during peak demand periods and improving cash conversion cycles (Fernaldy & Deniswara, 2025).

Challenges, Risks, and Implementation Strategies

The most frequently cited challenge in the literature is poor data quality, as inconsistent, incomplete, or unstandardized ERP data can significantly reduce AI model accuracy (Antonova et al., 2024; Raza, 2025). A second major barrier is the lack of human resource capability, including limited data literacy and reluctance to trust AI-generated outputs (Aktürk, 2021; Srbinoska & Donovska, 2023). High implementation costs and uncertain ROI expectations, particularly among SMEs, also present significant constraints (Wu, 2025).

Technical complexity in integrating AI with legacy ERP systems further complicates adoption (Martins & Marques, 2025). Cultural resistance is another critical factor, as employees may fear job displacement or distrust machine-generated recommendations (Caridi et al., 2026). Additionally, regulatory compliance and data security concerns remain unresolved, particularly due to the lack of standardized auditing frameworks for AI-driven financial decisions (Ranasinghe & Gide, 2025; Deloitte, 2026).

Key risks include cybersecurity threats, which may lead to financial and legal consequences, as well as decision errors caused by AI bias or hallucination. Vendor lock-in and workforce displacement also represent significant strategic risks (Antonova et al., 2024).

Effective implementation strategies identified in successful cases include a phased approach (crawl–walk–run), beginning with limited automation (e.g., anomaly detection), followed by supervised prescriptive analytics, and eventually progressing toward autonomous decision-making

(Raza, 2025). The human-in-the-loop approach is critical during transition phases, ensuring that AI recommendations are validated by financial experts before execution (Caridi et al., 2026).

Organizations are also advised to prioritize high-impact financial areas such as cash flow forecasting and fraud detection, where immediate benefits can be realized. Significant investment in data cleansing prior to implementation is essential but often underestimated (Deloitte, 2026). Furthermore, change management and intensive training are crucial to ensure that financial professionals understand AI outputs and can appropriately evaluate recommendations.

From an architectural perspective, the hybrid edge–cloud model is considered the most adaptive for current business environments characterized by volatility and the need for real-time responsiveness. This approach allows cost-efficient model training in the cloud while maintaining operational flexibility (Giantsidi & Tarantola, 2025).

Research Gap in Indonesia

Consistent with earlier findings, research on AI–ERP integration in Indonesia remains limited. Existing studies are primarily confined to specific industries, such as maintenance and repair operations, with only preliminary investigations into AI-based forecasting and ERP flexibility (Sipayung, 2025). Overall, AI awareness and adoption among Indonesian firms remain relatively low, indicating that many organizations have yet to fully leverage AI capabilities within ERP systems (Wu, 2025).

This gap presents significant opportunities for future research, particularly in developing context-specific best practices tailored to Indonesia's unique business environment, characterized by the dominance of SMEs, cultural diversity, and digital infrastructure challenges.

CONCLUSION

This study concludes that the integration of Artificial Intelligence (AI) into Enterprise Resource Planning (ERP) systems provides substantial contributions to enhancing organizational financial sustainability. Four primary architectural patterns were identified: embedded AI, add-on AI layers via API, hybrid edge–cloud models, and conversational AI assistants. Each architecture offers distinct advantages and limitations and is suitable for different organizational contexts (Aktürk, 2021; Antonova et al., 2024; Giantsidi & Tarantola, 2025; Ranasinghe & Gide, 2025).

Five key financial functions demonstrate the highest level of AI adoption: cash flow forecasting, anomaly and fraud detection, automated financial closing, working capital optimization, and narrative financial reporting (Singh, 2025; Middae et al., 2024; Oracle, 2025; Mannan et al., 2025; Dmitri, 2024). The implementation of AI–ERP systems significantly improves financial sustainability metrics, including enhanced forecasting accuracy, faster financial closing processes, improved fraud detection, and more efficient cash conversion cycles (Fernaldy & Deniswara, 2025; Raza, 2025; Gu, 2024).

Despite these benefits, key challenges persist, particularly related to poor data quality and limited human resource capabilities (Antonova et al., 2024; Raza, 2025). Significant risks include cybersecurity threats, erroneous decision-making due to AI bias or hallucination, and vendor dependency (Ranasinghe & Gide, 2025; Cherukuri & Yarram, 2024). Effective implementation strategies identified in the literature include a phased (crawl–walk–run) approach, maintaining human-in-the-loop oversight, prioritizing high-impact financial functions, investing in data cleansing, and implementing comprehensive change management and training programs (Caridi et al., 2026; Deloitte, 2026; McKinsey, 2026). Among the architectural options, the hybrid edge–cloud

model is considered the most adaptive for contemporary business environments characterized by volatility and real-time decision-making requirements (Giantsidi & Tarantola, 2025).

Research on AI–ERP integration in Indonesia remains limited, indicating substantial opportunities for future studies. Potential research directions include longitudinal and experimental studies, development of AI applications in financial management, mitigation of generative AI hallucination, contextual studies in non-manufacturing sectors, and investigations into AI–ERP adoption across Indonesian organizations (e.g., state-owned enterprises, SMEs, and regulatory bodies such as OJK and Bank Indonesia). Additionally, future research should explore the broader social implications of AI adoption, including workforce transformation, skill development, and algorithmic bias (Sipayung, 2025; Wu, 2025).

Ultimately, the success of AI–ERP implementation depends on high-quality data, strong top management support, and a carefully designed implementation strategy that continues to involve human judgment in critical decision-making processes.

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