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Integration, Innovation, and Development of Artificial Intelligence and Management Accounting

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Abstract: Quasi-financial state-owned enterprises, which refers to state-owned platforms engaged in financial leasing, financing guarantees, industrial funds, and related businesses, operate under the dual constraints of financial risk regulation and the preservation and appreciation of state-owned assets. Traditional manual management accounting suffers from static budgeting, lagging fund monitoring, passive risk response, and inefficient investment and financing estimation. Artificial intelligence can empower management accounting through dynamic fund monitoring, project return estimation, real-time risk early warning, and automated performance accounting of state-owned assets. Existing research focuses mainly on manufacturing enterprises or commercial banks and lacks a systematic framework tailored to the institutional characteristics of quasi-financial SOEs. From the practitioner perspective of finance executives in SOEs, this paper examines the integration logic and dedicated application scenarios of AI and management accounting, summarizes the innovative outcomes of integration across four dimensions, e.g., process, control model, investment and financing decision-making, and financial value, and analyzes the transformation challenges imposed by SOE budgeting, data, talent, and internal-control constraints. It proposes five optimization paths: phased technology implementation, comprehensive data governance, cultivation of interdisciplinary talent, dual risk control over data and algorithms, and dynamic system iteration, offering practical reference for the digital integration of business and finance and intelligent fund management in comparable SOEs.

Keywords: artificial intelligence; management accounting; quasi-financial state-owned enterprises; intelligent finance; digital transformation

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1. Introduction

Quasi-financial SOEs are primarily engaged in debt financing, equity investment, and guarantee businesses; they are characterized by rapid capital turnover and pronounced leverage, and must simultaneously satisfy the assessment requirements of both state-owned asset regulators and local financial regulators. Traditional management accounting relies on manual ledgers for annual budget preparation, ex-post revenue accounting, and quarterly regulatory reporting. Data on fund positions, customer delinquencies, and capital occupation are updated with delay, so that interest-rate fluctuations and industry-wide clustered defaults can readily trigger impairment losses of state-owned assets.

As the digital transformation of SOEs advances, AI-based risk management has become a focus of financial informatization, and technologies such as big data, cloud computing, and machine learning have become deeply involved in financial risk prediction and the evolution of accounting information systems (Xu & Zhang, 2025). Embedding AI throughout the entire chain of budgeting, funds, investment and financing, risk management, and performance evaluation is the core pathway for coordinating business expansion, compliance risk control, and the preservation and appreciation of state-owned capital. Examining this integration in light of the industry's dual regulatory characteristics carries significant theoretical and practical value.

International research focuses mainly on credit algorithm models for market-based financial institutions. Systematic reviews show that machine learning has come to dominate

credit risk assessment, with deep learning and ensemble methods generally outperforming traditional statistical models in default prediction (Alonso-Robisco & Martínez, 2022; Shi et al., 2022). Another strand of literature examines the transformation AI brings to management accounting decision support, finding that it significantly enhances predictive analytics capabilities and automates reporting (Pavlović et al., 2024), drives the construction of AI forecasting models for strategic decision support (Ye, 2025), and gives rise to new models such as "intelligence + accounting" and "intelligence + financial shared services" (Che et al., 2024). Domestic research, by contrast, concentrates mostly on cost control in manufacturing and the application of financial RPA in general enterprises (Oyeniyi et al., 2024; Yao, 2024), as well as accounting digital transformation and financial shared services (Zhu, 2023; Wu, 2025). Some studies also note that SOEs face longer transformation cycles and tighter staffing constraints, with greater resistance in building a culture of digital innovation and accumulating digital skills (Guo & Polák, 2024). Neither strand of research, however, addresses the institutional reality of quasi-financial SOEs: state-owned asset appraisal, internal approval procedures, and dual regulation extend beyond the explanatory scope of models built for commercial banks or manufacturing firms, and dedicated studies targeting guarantee companies, financial leasing, and industrial funds remain scarce.

Existing research has evident gaps: it emphasizes technical tools while neglecting the integration mechanism under dual regulation; scenario analyses are fragmented and lack a complete analytical framework; and proposed measures are highly generic, failing to account for real constraints such as SOE budgeting, organizational staffing, and data access authority. This paper proceeds from the frontline management perspective of finance executives to address these gaps. The study unfolds along the chain of "integration logic—application scenarios—innovative outcomes—practical challenges—optimization paths—conclusions and outlook." Its theoretical contribution lies in constructing an integration framework that balances financial risk control with state-owned asset management, while its practical contribution lies in proposing low-cost, tiered digital implementation paths grounded in the realities of SOE approval, budgeting, and staffing.

2. The Integration Logic

2.1 The Internal Logic of Integration

Technology enablement logic. AI engages management accounting through three technical mechanisms. Robotic process automation executes rule-based, high-frequency tasks such as data entry, interest calculation, and report generation with greater speed and fewer errors, freeing finance staff from repetitive work (Ayinla et al., 2024). Machine learning extracts predictive signals from historical data, supporting predictive analyses—such as default risk assessment—that traditional methods struggle to perform. Data-middle-platform architectures connect business, risk, and financial systems to enable the collection, mining, and visualization of massive operational data (Wang & Dai, 2025).

Function expansion logic. Quasi-financial SOEs generate large volumes of daily data on lending, compensation, credit extension, and fund settlement, which manual accounting processes slowly and error-prone. Through RPA-based automatic data extraction, machine-learning estimation, and real-time indicator dashboards, repetitive tasks such as interest calculation, report preparation, and budget estimation are automated, shifting the management accounting function from passive recording toward continuous prediction and advance warning—consistent with research findings that intelligent systems provide real-time insights and significantly improve prediction accuracy.

Value enhancement logic. Traditional management accounting centers on ex-post accounting, static budgeting, and periodic reporting. AI connects business, risk, financial, and state-owned asset systems, adding functions such as fund shortfall alerts, dynamic project return estimation, customer default rating, and rolling forecasts of state-owned asset indicators. Management thus extends from ex-post statistics to full-cycle fund control, and the value orientation of management accounting shifts toward the preservation and appreciation of state-owned capital and forward-looking risk prevention (Han, 2026).

2.2 Dedicated Application Scenarios

Finance departments are no longer confined to back-office accounting and compliance reporting. AI-driven mining of multidimensional operational data can identify inefficient assets, idle funds, and high-risk businesses, providing quantitative foundations for capital allocation, fund deployment, and fund planning. Six specific scenarios emerge.

Multi-scenario budgets are automatically generated by integrating historical operational and assessment data; disbursement and compensation data are synchronized in real time and budget variances computed automatically, adapted to

SOE budget filing and state-owned asset approval processes. Such AI-driven forecasting models have been shown to significantly improve the efficiency and accuracy of management accounting planning.

Data from all funding channels are aggregated to estimate overall funding costs in real time, forecast medium- and long-term cash flows, alert on fund shortfalls and idle funds, and optimize liquidity allocation, building on AI's capacity to process massive data rapidly and update forecasts continuously.

Estimation models for financial leasing, guarantees, and funds are constructed to conduct multi-scenario IRR and return-on-capital calculations and simulate industry and interest-rate stress scenarios, supporting pre-investment review and state-owned asset filing. Credit risk research shows that machine learning and ensemble models significantly outperform traditional scoring methods in default prediction, with ensemble gradient boosting trees and random forests (Li et al., 2025).

Regulatory thresholds such as non-performing ratios, customer concentration, and leverage ratios are embedded into the system; when indicators breach thresholds or clustered delinquencies occur, early-warning work orders are automatically pushed to enable early risk identification. Machine-learning credit monitoring based on dynamic transactional information provides the analytical engine for such early-warning mechanisms (Injadat et al., 2021).

Indicators such as the preservation and appreciation rate, return on net assets, and reduction of non-performing assets are automatically collected to generate multidimensional performance reports with one click and quantify the contribution of each business segment, echoing the finding in public finance digital transformation that automated systems improve budget monitoring and transparency (Teixeira et al., 2025).

Macro-policy and industry-benchmark data are integrated to estimate the returns and risks of strategic options such as capital increases, guarantee capacity expansion, and business contraction, providing quantitative support for board-level capital planning.

3. Innovative Outcomes of the Integration of AI and Management Accounting

Before transformation, business, fund, and financial systems operated independently, and finance staff reconciled data manually, making report preparation time-consuming and error-prone. After the data middle platform was established, systems interact in real time, and RPA automatically completes interest calculation, provision estimation, and the preparation of state-owned asset and regulatory reports. Research confirms that RPA significantly shortens reporting cycles and reduces human errors in posting, reconciliation, and compliance checks (Harshitha & Ramya, 2025), while automation in financial reporting yields systematic gains in efficiency, accuracy, and scalability (Alao et al., 2024). Month-end and quarter-end closing cycles are noticeably shortened, and compliance risk in data filing declines.

Under the traditional model, losses and provisions could only be computed after a project had deteriorated or a customer had defaulted, by which time the loss was an accomplished fact. With AI integrated, a closed-loop management model emerges: pre-investment, the intelligent system estimates access thresholds; during the holding period, it monitors repayments, credit records, and regulatory indicators in real time and intervenes early when risk signals appear; and at year-end, it reviews asset returns and non-performing assets and feeds the results back into the following year's investment criteria. Dynamically assessing borrower credit on the basis of transaction history is precisely the core capability that machine-learning credit risk systems provide to this closed loop.

In the past, investment review and capital planning relied on managerial experience and lacked quantitative risk–return estimation, readily leading to inefficient capital allocation and the accumulation of high-risk exposures. Intelligent systems automatically generate multi-scenario estimation reports and benchmark them against regulatory and state-owned asset assessment thresholds, enabling managers to compare alternatives on objective data. Such decision support systems have been confirmed to deliver real-time insights and enhance the effectiveness of strategic decision-making, reducing the risk of state-owned asset losses caused by subjective decisions through quantitative evidence.

Before digitalization, finance departments focused mainly on bookkeeping, tax filing, and report submission and rarely participated in front-end business evaluation. AI frees staff from routine accounting work, allowing management accounting teams to participate deeply in investment review, fund allocation, and risk assessment—identifying inefficient assets, optimizing funding structures, reducing non-performing assets, and proactively proposing fund

optimization plans—and to become the core department coordinating state-owned capital operations and safeguarding financial risk bottom lines. Moving from a compliance orientation toward strategic value creation is a hallmark of finance transformation in the digital economy (Schröder, 2026), and the management accounting profession is consequently evolving toward a data-driven, decision-oriented role (Arkhipova et al., 2024).

4. Practical Challenges to the Integration of AI and Management Accounting

The translation of these innovations from blueprint into practice must confront the constraints peculiar to quasi-financial SOEs, concentrated in four areas: technology, data, talent, and institutions.

4.1 Shallow Application and Fragmented Legacy Systems

Most enterprises have implemented only basic RPA functions such as invoice recognition, while core modules such as investment and financing modeling and intelligent risk control remain unformed. Intelligent middle platforms require substantial investment, yet informatization budgets must be filed annually with state-owned asset regulators for approval, so construction can only proceed in phases. Legacy leasing and guarantee systems generally lack standardized interfaces, making integration with the financial middle platform difficult; differences among subsidiaries further complicate deployment of a unified platform. The complexity of system integration and the friction of personnel adaptation are well documented in the automation literature, and are particularly pronounced in SOEs with longer transformation cycles and constrained resource allocation.

4.2 Prominent Data Silos and a Lack of Governance Systems

Data standards differ across systems—for example, inconsistencies between business disbursement volumes and financial interest-bearing asset calibers directly impair the accuracy of AI estimation. Enterprises have no dedicated data governance positions, raw business and financial data are incomplete and updated with delay, and state-owned asset performance data require manual adjustment. Sensitive data such as credit information and delinquency exposures are subject to access restrictions, further fragmenting the data chain. This problem is general: surveys show that 82% of data executives struggle to provide stable, reliable data streams for decision-making, and most organizations do not link data quality to performance appraisal (Yukhno, 2022). Management accountants likewise regard data accuracy, reliability, and completeness—along with the skills to handle massive unstructured data—as the foremost professional challenges of the digital era.

4.3 Shortage of Interdisciplinary Talent under Staffing and Compensation Constraints

Existing finance staff are familiar with SOE accounting but lack financial modeling and AI system skills; risk control staff understand credit operations but lack knowledge of management accounting and state-owned asset appraisal rules. The industry urgently needs interdisciplinary talent combining accounting, finance, and digital skills, but SOE staffing and compensation systems constrain the recruitment of high-end talent, internal digital training is insufficient, and employees have limited motivation for self-directed learning. The digital skills gap is a general bottleneck in digital transformation (Joel et al., 2024), and demand for AI, data analytics, and cybersecurity talent in the financial sector is growing faster than supply (Chahal, 2023).

4.4 Lagging Internal Control and Dual Data–Algorithm Risks

There is still no unified industry standard for intelligent finance and AI-based risk management. Existing institutions are designed around manual processes and do not define responsibilities for intelligent system operations or procedures for responding to early warnings. Cloud-based storage of sensitive customer data carries risks of leakage and tampering. AI models rely on historical data, and their accuracy may decline when the macroeconomic environment changes, yet enterprises have not established routine algorithm validation mechanisms. Generative AI is particularly notable for risks such as hallucinated details and optimism bias, requiring structured verification arrangements (Abdelouahab et al., 2025; Jones & Free, 2026). Automatically generated reports also lack graded manual review, creating compliance risks in filing. Audit research likewise warns that generative tools demand rigorous professional oversight and professional skepticism (Zhang & Zhou, 2025), even as large language models find increasingly broad application in disclosure and reporting practice (Dong et al., 2024).

5. Pathways for Deepening the Integration of AI and Management Accounting

5.1 Implement Intelligent Systems in Layers and Phases, Adapted to SOE Budgetary Constraints

In the short term, prioritize lightweight tools such as fund estimation and report automation, and upgrade interfaces in legacy systems to connect core data. In the medium and long term, leverage dedicated state-owned asset digital transformation budgets to build an integrated business–finance middle platform covering investment and financing modeling, intelligent early warning, and automated performance evaluation. The group can deploy the platform centrally while subsidiaries adopt lightweight SaaS solutions to reduce costs, with annual budgets reserved for system iteration and continuous model optimization. Gradual, phased introduction rather than wholesale replacement is the prudent approach generally recommended in the literature, and is especially applicable to SOEs with structural transformation cycles and resource constraints.

5.2 Establish an Enterprise-Wide Data Governance System and Unify Business, Financial, and State-Owned Asset Data Calibers

Business, risk, financial, and state-owned asset departments jointly define company-wide standard statistical calibers. Data governance positions are established through internal transfers to circumvent staffing constraints, together with routine mechanisms for data collection, validation, and cleansing. A tiered-access data middle platform balances data sharing against customer information confidentiality. Data completeness and accuracy are incorporated into business department performance appraisals to improve data quality at the source. Linking data quality to performance appraisal is a mechanism confirmed in the data governance literature, and a sound governance framework is a precondition for trustworthy AI output.

5.3 Combine Internal Cultivation with Flexible External Recruitment to Build an Interdisciplinary Talent Pool

Internally, deliver tiered digital training: basic finance staff learn intelligent system operations, while management receives advanced training in financial modeling and algorithm-based risk control; implement job rotation between finance and risk control positions to accumulate cross-functional capability. Externally, bring in digital experts on project-based contracts that do not occupy formal headcount, establish targeted cultivation channels with finance and economics universities, and incorporate digital achievements into finance staff promotion criteria. Increased training investment and retention arrangements are widely regarded as the principal means of closing the digital skills gap, and finance transformation overall demands a profound change in financial skills and culture.

5.4 Strengthen Intelligent Internal Control and Build Dual Data–Algorithm Risk Control

Revise budgeting, investment and financing, risk management, and performance management institutions to define graded review requirements for AI-estimated data and procedures for handling early-warning work orders. Establish data security mechanisms through encrypted local storage, tiered access, and operation audit trails. Conduct quarterly stress tests of return and early-warning models, with AI estimates and warnings double-checked by both finance and risk control staff. State-owned asset and regulatory reports may only be filed after two-level review by the responsible supervisor and the chief financial officer. Continuous human oversight of AI is the precondition for responsible application, and retaining professional judgment within the human-in-the-loop is the core safeguard against algorithmic errors and bias (Vasarhelyi et al., 2023).

5.5 Iterate Management Accounting Systems Dynamically to Adapt to Regulatory and Technological Evolution

State-owned asset appraisal and financial regulatory rules change continuously, and intelligent management accounting systems must be optimized accordingly. As large language models gain ground in financial reporting and decision support, estimation and early-warning models should be updated in step with advances in generative AI and big data technologies; system thresholds should be revised synchronously when regulatory indicators change; and operational problems such as fund mismatches and inefficient investment should be reviewed periodically with progressively refined analytical dimensions. Given the rapid evolution of the technology itself, continuously updating models while maintaining professional oversight is the only way to sustain the value of fund control and risk prevention.

6. Conclusions

From the perspective of finance executives in quasi-financial SOEs, this paper reaches four core conclusions. First, AI can be deeply integrated into management accounting through three mechanisms—technology enablement, function expansion, and value enhancement—covering six scenarios: budgeting, funds, investment and financing, risk management, performance evaluation, and capital decision-making, consistent with the industry's capital-intensive, dual-regulated, high-risk characteristics and the requirement of state-owned asset preservation and appreciation. Second, the integration produces four innovations—process automation, full-cycle closed-loop management, data-driven decision-

making, and finance function upgrading—effectively resolving the traditional problems of lagging control, distorted estimation, ex-post risk handling, and inefficient fund deployment in management accounting. Third, current transformation faces industry-specific challenges including shallow application, data silos, interdisciplinary talent shortages, inadequate internal-control support, and data–algorithm security risks. Fourth, the five pathways of phased technical advancement, comprehensive data governance, tiered talent cultivation, dual risk-control mechanisms, and dynamic system iteration should be adopted to coordinate SOE institutional requirements, financial compliance, and state-owned asset assessment, achieving capital appreciation under controllable risk. The integration of AI and management accounting is thus not merely an upgrade of financial tools but a systematic transformation of fund management, risk prevention, and the value management of state-owned assets—a view consistent with the academic consensus that intelligent finance must strengthen internal control and continuously upgrade accounting systems, and a key lever for SOE digital transformation and the prevention of regional financial risks.

As digital appraisal of state-owned assets and AI-based financial modeling mature, the integration of intelligent management accounting will continue to deepen: AI may achieve autonomous full-cycle project estimation and generate risk-response plans; regulatory systems may connect directly with enterprise intelligent middle platforms for automated filing; the industry may issue unified standards for intelligent finance in state-owned leasing and guarantee enterprises; and interdisciplinary talent combining financial, risk-control, and digital literacy may become the norm. In the long run, intelligent management accounting will run through the entire chain of capital allocation, risk resolution, and asset appreciation, coordinating the three operational objectives of serving the real economy, preventing risks, and appreciating state-owned assets. Future research may conduct case studies on dedicated business models such as guarantees and financial leasing to further refine differentiated digital implementation plans.

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