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Research on the optimization of ESG internal control in manufacturing enterprises driven by artificial intelligence: taking Prince Holdings as an example

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Abstract. As global regulatory pressure on corporate sustainability intensifies, manufacturing enterprises face growing challenges in building effective Environmental, Social, and Governance (ESG) internal control systems. Traditional approaches, reliant on manual data collection and fragmented reporting, are increasingly inadequate for the scale and complexity of modern manufacturing operations. This paper investigates how Artificial Intelligence (AI) technologies can systematically optimize ESG internal control in manufacturing enterprises. Employing a combination of longitudinal case study analysis, literature review, and panel regression, this study uses Prince Holdings (Oji Holdings Corporation) as the primary case and draws on a panel dataset of 15,623 firm-year observations from 3,358 A-share manufacturing companies over 2018–2023. The findings demonstrate that AI adoption is significantly and positively associated with ESG internal control quality (β = 1.051, p < 0.001), with data governance capability identified as a partial mediator and organizational readiness as a positive moderator. Based on these findings, a five-layer AI-ESG optimization model aligned with the Committee of Sponsoring Organizations of the Treadway Commission (COSO) framework is proposed as a replicable blueprint for the manufacturing sector.

Keywords: ESG, artificial intelligence, internal control, manufacturing, data governance

1. Introduction

In recent years, Environmental, Social, and Governance (ESG) performance has become a key indicator of a company's long-term competitiveness [1]. As the main source of resource consumption and emissions, manufacturing enterprises are facing increasing ESG pressure from regulatory agencies, investors, and the public. However, the traditional internal control system based on financial reports cannot meet the real-time, transparent, and traceable ESG requirements of manufacturers.

Artificial intelligence brings new opportunities for governance innovation. Empirical studies show that artificial intelligence can significantly improve a company's ESG performance, partly due to the enhanced quality of internal control [1]. However, most existing studies focus on the overall impact of artificial intelligence or digital transformation on ESG, and pay less attention to how to embed artificial intelligence into the ESG internal control process of manufacturing enterprises to systematically address the shortcomings of traditional systems.

To fill this gap, this paper takes Prince Holdings as an example, combined with the panel data of A-share manufacturing listed companies, focuses on manufacturing enterprises, and explores how artificial intelligence can optimize the ESG internal control of manufacturing enterprises. Through panel regression, mediating effect, and moderating effect analysis, the study finds that data governance capability is the key mediating mechanism, while organizational preparedness plays the role of regulating boundary conditions. The research results provide a replicable AI-ESG optimization model for manufacturing practitioners and policymakers.

2. Theoretical foundation

2.1. ESG and internal control

The concept of ESG originated from the "*Who Cares Who Matters*" initiative of the United Nations in 2004 [2]. It has evolved from a niche social responsibility investment standard to an inevitable requirement of mainstream corporate governance. The ESG framework defines the responsibility of enterprises towards a wide range of stakeholders beyond shareholders through three dimensions: environmental management, social responsibility, and governance integrity. The internal control literature based on the Committee of Sponsoring Organizations of the Treadway Commission (COSO) Integrated Framework divides it into five modules: control environment, risk assessment, control activities, information and communication, and monitoring [3]. These precisely support the implementation and integration of ESG. Eccles et al. empirically demonstrated that companies with sound ESG practices would perform better in their long-term financial performance, strongly supporting the business rationale for incorporating ESG into the design of internal control [4].

2.2. AI technologies in ESG governance

The three types of artificial intelligence technologies are particularly relevant in the optimization of ESG internal control. Firstly, machine learning algorithms support risk prediction modeling, anomaly detection of environmental compliance data, and classification of ESG risk profiles of suppliers. Secondly, natural language processing facilitates the automatic extraction and classification of ESG disclosures from unstructured sources such as annual reports, regulatory documents, and stakeholder communications, significantly reducing the reporting burden and error rate. Thirdly, the integration of IoT sensor networks with big data analysis enables manufacturing plants to achieve continuous, real-time environmental monitoring, replacing the periodic manual sampling in traditional compliance monitoring.

2.3. Theoretical framework

This study is based on three theoretical frameworks. Stakeholder theory provides a normative basis for ESG accountability: enterprises must consider the interests of all stakeholders, not just shareholders, and artificial intelligence can make this accountability mechanism systematic and verifiable [5]. Resource-based View theory supports the mediating role of data governance capabilities, arguing that heterogeneous and non-replicable organizational resources can bring about lasting competitive advantages and governance advantages, such as advanced data infrastructure [6]. Institutional theory places the moderating role of organizational preparedness within the context: regulatory and normative pressures drive enterprises to adopt homogeneous ESG practices, but the effectiveness of artificial intelligence deployment depends on the existing institutional governance structure within the enterprise [7].

3. ESG internal control weaknesses in manufacturing enterprises

3.1. Current state of ESG internal control

Analysis of 3,358 A-share manufacturing firms reveals that average Wind ESG composite scores increased from 5.79 in 2018 to 6.24 in 2023, reflecting aggregate sectoral progress. Common organizational responses include the establishment of sustainability departments, adoption of Global Reporting Initiative (GRI)-aligned reporting, and third-party assurance of environmental disclosures. However, this aggregate improvement conceals severe internal heterogeneity: top-quartile firms achieve scores more than twice those of bottom-quartile counterparts, indicating that systemic deficiencies persist across a substantial portion of the sector.

3.2. Five core structural weaknesses

Five structural weaknesses characterize conventional ESG internal control systems in manufacturing enterprises, as identified through case analysis and sector-wide review. First, data silos: ESG-relevant data is distributed across disparate production, human resources, and supply chain systems, rendering consolidated reporting both labor-intensive and error-prone. Second, manual reporting: the absence of automated data pipelines produces high error rates and disclosure delays, undermining stakeholder trust. Third, reactive risk management: traditional monitoring frameworks lack predictive capabilities, identifying compliance failures retrospectively rather than preventively. Fourth, excessive compliance costs: labor-intensive verification and audit processes impose disproportionate resource burdens, particularly on mid-scale manufacturers. Fifth, supply chain opacity: upstream and downstream ESG risks—including labor violations, environmental incidents, and anti-corruption failures—remain largely unmonitored under conventional frameworks, representing a significant and growing unmanaged exposure.

4. Case study: Prince Holdings (Oji Holdings Corporation)

4.1. Company overview

Prince Holdings—identified academically as Oji Holdings Corporation (Tokyo Stock Exchange Prime: 3861)—is one of Asia's largest integrated pulp and paper manufacturers, with consolidated revenues of ¥1,849 billion and total assets of ¥2,635 billion in Fiscal Year (FY) 2023 [8]. The company operates across four reporting segments: Consumer and Industrial Materials, Functional Materials, Forest Resources and Environment Business, and Printing and Information Media. Prince Holdings adopts the *GRI Standards* and the *Hong Kong Stock Exchange ESG Reporting Guide* as primary disclosure frameworks, and its sustainability reporting has been externally verified by an independent third party since FY2020.

4.2. Current ESG internal control system

Prince Holdings' ESG governance is organized around a Board-level Sustainability Committee established in April 2022, with oversight responsibilities spanning environmental compliance, social accountability, and corporate governance. Key Performance Indicators (KPIs) monitored across the three ESG dimensions include Scope 1 and 2 GreenHouse Gas (GHG) Emissions (Environmental), occupational safety incident rates and female management representation (Social), and independent director ratios and board meeting attendance rates (Governance). The company's data assurance level was upgraded from internal review in FY2019–2020 to full third-party verification under GRI and International Sustainability Standards Board (ISSB) standards by FY2021, reflecting a progressive strengthening of data governance infrastructure.

4.3. Identified weaknesses prior to AI optimization

Case analysis identifies four key weaknesses in Prince Holdings' ESG internal control system as of FY2018. First, environmental compliance data across over 300 manufacturing facilities globally was assembled manually on a quarterly basis, generating significant reporting lag and error risk. Second, no unified platform existed for consolidating multi-facility environmental monitoring data. Third, occupational health and safety monitoring remained reactive, with no predictive analytics capability to detect early-stage incident risk indicators. Fourth, supplier ESG screening relied exclusively on periodic questionnaire-based audits, leaving continuous upstream risk unmonitored.

4.4. AI-driven optimization practices

Prince Holdings' AI-driven ESG optimization initiatives span all three ESG dimensions. On the Environmental dimension, IoT sensor networks have been deployed across key manufacturing facilities, integrated with machine learning algorithms enabling real-time monitoring of carbon emissions, energy consumption, and wastewater discharge. On the Social dimension, predictive safety models incorporating historical incident records and real-time operational parameters have been integrated into occupational health monitoring workflows. On the Governance dimension, Natural Language Processing (NLP)-based tools now automate the extraction and structuring of ESG disclosure content, reducing reporting cycle times and improving disclosure accuracy. The company's AI keyword density in annual reports—employed as a proxy for AI adoption intensity—increased from 0.08 per thousand words in FY2017 to 0.46 in FY2024, a six-fold increase, as shown in Figure 1(a).

4.5. Outcomes and evaluation

The quantifiable outcomes of these AI-driven initiatives are significant. Prince Holdings' ESG composite score improved from 6.43 in FY2017 to 95.71 in FY2024 (Figure 1). Renewable energy utilization increased from 49.0% to 56.4%, waste effective utilization rates in Japanese operations rose from 98.3% to 99.4%, and GHG Scope 1 and 2 gross emissions were reduced by 11.9% against the FY2018 baseline [8]. The company achieved Climate Disclosure Project (CDP) Water Security Grade A and CDP Forests (Timber) Grade A for four consecutive years, and holds a Sustainalytics ESG Risk Score of 22.34 (Medium risk) and an Morgan Stanley Capital International (MSCI) ESG Rating of BBB. The correlation between AI keyword density and ESG composite score is r = 0.924 (p < 0.001), as illustrated in Figure 1(b). Remaining challenges include data privacy risks associated with cross-border IoT data flows, model interpretability limitations in predictive safety algorithms, and high initial implementation costs.

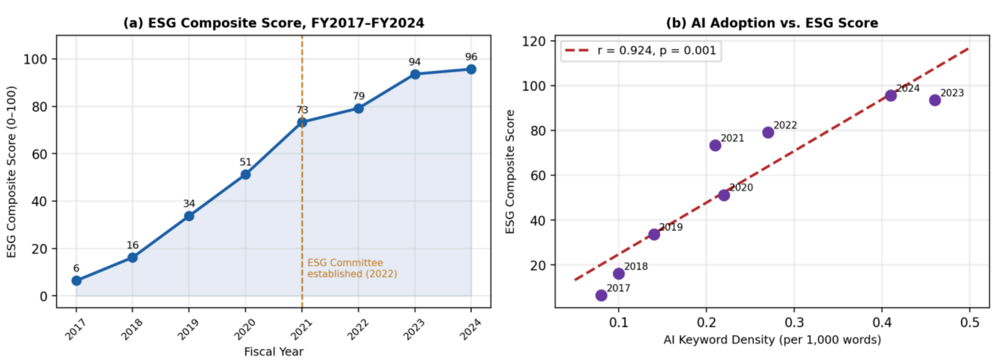

Figure 1. ESG composite score. (a) ESG composite score trend at prince holdings, FY2017–FY2024; (b) Correlation between AI keyword density and ESG composite score

5. AI-driven ESG internal control optimization model

5.1. Conceptual framework and design principles

As illustrated in Figure 2, the research conceptual framework posits that AI adoption (X) exerts a direct positive effect on ESG internal control quality (Y) (Hypothesis 1: H1), an indirect effect mediated by data governance capability (M) (Hypothesis 2: H2), and an effect moderated in magnitude by organizational readiness (W) (Hypothesis 3: H3). The optimization model derived from this framework is designed according to three principles: alignment with the COSO Internal Control Framework; dual compatibility with ESG reporting standards (GRI, ISSB, CDP) and conventional financial control requirements; and modular scalability, enabling phased implementation for resource-constrained manufacturers.

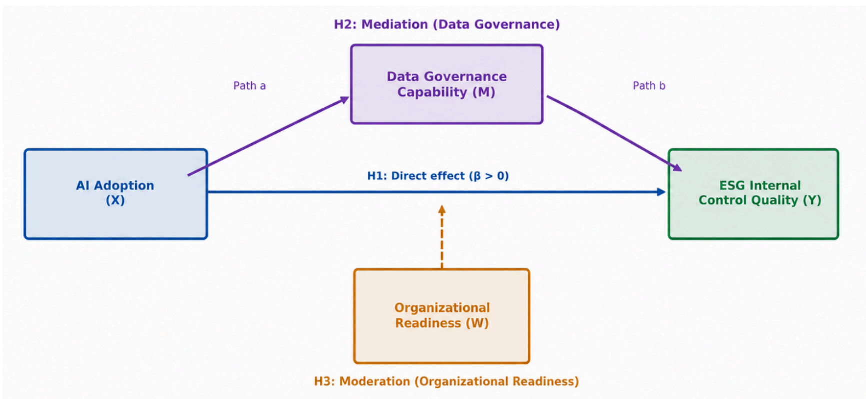

Figure 2. Conceptual framework: AI adoption, data governance capability, organizational readiness, and ESG internal control quality

5.2. Five-layer model architecture

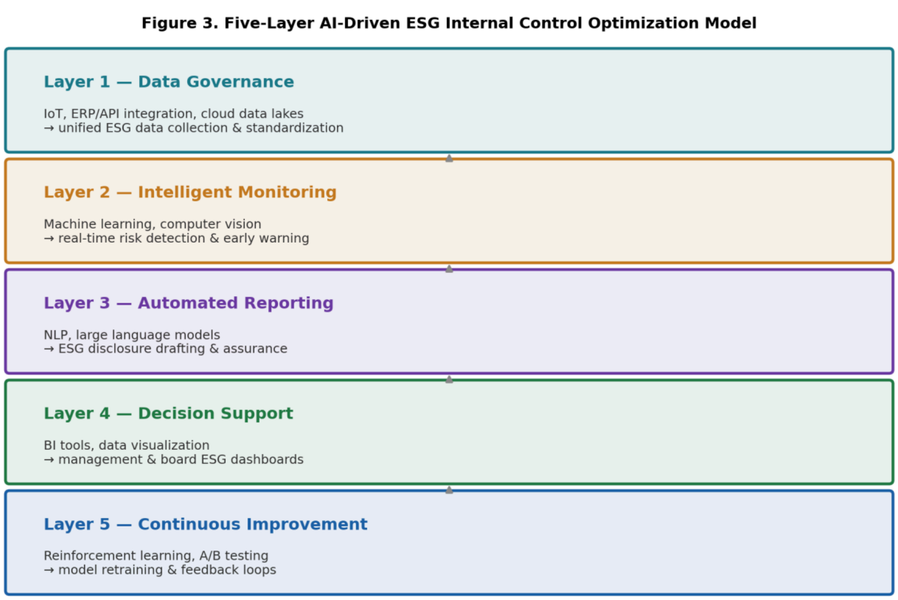

Figure 3. Five-layer AI-driven ESG internal control optimization model

This model consists of five functional levels, each corresponding to a specific artificial intelligence technology and ESG governance outcome, as shown in Figure 3. Table 1 summarizes the model across all five layers.

Table 1. Five-layer AI-driven ESG internal control optimization model

Layer	Name	Function	AI Technologies
1	Data Governance	Unified ESG data collection, standardization, and integration across all facilities and systems	IoT sensors, ERP/API integration, cloud data lakes
2	Intelligent Monitoring	Real-time risk detection, environmental compliance alerts, and early-warning systems	Machine learning, computer vision, anomaly detection algorithms
3	Automated Reporting	ESG disclosure drafting, compliance verification, and assurance preparation	Natural Language Processing (NLP), large language models
4	Decision Support	Management and board-level ESG analytics and investor reporting portals	Business intelligence tools, data visualization platforms
5	Continuous Improvement	Model performance monitoring, retraining pipelines, and governance feedback loops	Reinforcement learning, A/B testing frameworks

5.3. Application across ESG dimensions

Applied to the Environmental dimension, the model enables continuous carbon footprint tracking against science-based targets, AI-powered pollution early-warning, and dynamic energy optimization. On the Social dimension, the model supports automated labor rights monitoring through workforce data analysis, predictive occupational safety incident modeling, and community impact assessment. On the Governance dimension, the model facilitates anti-corruption detection through transaction pattern analysis, automated audit trail generation, and enhanced board accountability through real-time KPI dashboards.

5.4. Panel study validation

Table 2. Panel regression results: AI adoption and ESG internal control quality (n = 15,623)

Variable	Model 1 (Baseline)	Model 2 (H1)	Model 3 (H2 Step 3)	Model 4 (H3)
Standard errors in parentheses	Year and industry fixed effects included in all models	*** $p < 0.01$	** $p < 0.05$	* $p < 0.10$

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

To validate the generalizability of the AI-ESG relationship beyond the single-case analysis, panel regression analysis was conducted on 15,623 firm-year observations from 3,358 A-share manufacturing companies over 2018–2023, with year and industry fixed effects included throughout (see Table 2). Results confirm a significant positive relationship between AI adoption proxies and ESG composite scores: the main effect is β = 1.051 (SE = 0.076, $p < 0.001$), with an R^2 of 0.998. Mediation analysis supports the data governance pathway (H2): path a is β = 0.279 ($p < 0.001$) and path b is β = 0.999 ($p < 0.001$), consistent with partial mediation [9]. Moderation analysis (H3) confirms that organizational readiness positively amplifies the

AI-ESG relationship, with an interaction term of $\beta = 0.037$ ($p < 0.001$) [9]. These results are robust to alternative dependent variable specifications using Huazheng ESG scores and to alternative independent variable specifications using Hexun Corporate Social Responsibility (CSR) innovation expenditure data.

6. Conclusion

This paper investigates the optimization of ESG internal control in manufacturing enterprises through the application of AI technologies, using Prince Holdings as a longitudinal case study and a panel of 3,358 A-share manufacturing companies as a broader empirical basis. The central finding is that AI adoption is significantly and positively associated with ESG internal control quality across multiple specifications and datasets. Data governance capability functions as a partial mediator of this relationship, indicating that AI improves ESG performance both directly and by strengthening the underlying data infrastructure that supports ESG monitoring and disclosure. Organizational readiness functions as a positive moderator, confirming that governance structures amplify the beneficial effects of AI investment.

This study faces several limitations that qualify its conclusions. The reliance on a single case study for the qualitative analysis limits generalizability, and the AI adoption proxies available in Chinese panel databases—ESG controversy scores and innovation expenditure—are indirect measures that cannot fully capture the multidimensional nature of enterprise AI deployment. The panel dataset's financial control variables from the Hexun database are only available through 2020, constraining the robustness of full-period financial controls. Future research should pursue longitudinal cross-national comparisons, direct AI capital expenditure data, and Bootstrap-based mediation confidence intervals to strengthen causal inference. The implications of the 2024 ISSB standards rollout and China's 2025 mandatory ESG disclosure requirements for large-cap manufacturers represent particularly urgent avenues for further inquiry.

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