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Application of Intelligent Financial Management System Based on Artificial Intelligence in Textile and Garment Enterprises

Min Zhang[1*], Min Huang[2]
[1]College of Business, NanNing University, Nanning City 530000, Guangxi, China
[2]Shiyuan College, Nanning Normal University, Nanning City 530001, Guangxi, China
*13978878846@163.com

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ABSTRACT
Textile and apparel enterprises face persistent operational challenges, including complex production cost structures and volatile raw material markets. To address these challenges, this study investigates the efficacy of integrated production and cost control systems based on artificial intelligence in such enterprises. This study utilizes a quasi-experimental design, using propensity score matching (PSM) to compare 60 textile and apparel enterprises (a treatment group of 30 adopters and a control group of 30 non-adopters), supplemented by qualitative case studies to uncover the underlying mechanisms of performance variation. Results reveal that firms adopting these advanced manufacturing process management systems exhibit significantly improved production economics. By enhancing the integration of procurement, production, and cost-tracking processes, these enterprises achieve superior operational efficiency, marked by substantial raw material procurement cost savings and a sharp reduction in inventory obsolescence and material waste. Qualitative results further confirm that the application of such systems enables a shift toward proactive control over material flows and production scheduling, resulting in markedly more accurate alignment with manufacturing cost targets. This study concludes that integrated process control systems are not only essential for enhancing manufacturing profitability in the textile and apparel industry but also strengthen operational resilience and strategic production planning, offering compelling evidence of these systems' transformative role in the sector's modernization.

KEYWORDS
garment manufacture, textile engineering, production cost engineering, materials management textile and garment enterprises

INTRODUCTION

Amidst the accelerating tides of globalization and digital transformation, the textile and apparel industry—a quintessential representative of traditional manufacturing—is encountering unprecedented operational pressures and structural transformation challenges [1,2]. Financial management within this sector has become increasingly intricate, characterized by substantial uncertainty in cost control and narrowing profit margins, continuously compressed by fluctuations in raw material prices and increasing labor expenses. Volatility in the prices of essential raw materials, such as cotton, which are highly susceptible to extreme weather events and international trade policies, has considerably complicated procurement cost management [3,4]. Simultaneously, escalating labor costs, particularly in labor-intensive manufacturing regions, such as Southeast Asia, have further eroded the profit margins of industry participants [5,6].

The textile and apparel industry's defining features—short product life cycles, pronounced seasonality, and rapidly evolving fashion trends—further exacerbate operational complexity [7,8]. In particular, inventory management remains a critical pain point. For example, ZARA attaches immense importance to inventory management. It uses advanced algorithms and AI technology to predict seasonal demand trends, adopts the "just-in-time" (JIT) production mode to avoid overproduction, and implements time-limited discounts, bundled sales, or flash sales for slow-moving goods through AI (Artificial Intelligence, is a discipline and technological field that studies how to enable computer systems to perform tasks that typically require intelligence akin to that of Homo sapiens.) analysis of inventory and sales data [9]. Outdated products are frequently offloaded through deep discounting or outright destruction, causing severe economic losses. Furthermore, the proliferation of omnichannel retailing has necessitated the integration of heterogeneous financial data from e-commerce platforms, brick-and-mortar outlets, and social media sales channels. Traditional financial management methods often rely on historical data and subjective judgment, resulting in such issues as delayed responses, low efficiency, and lack of scientific basis for decision-making [10]. Although some financial management software systems exist in the market with independent functional modules, they fail to achieve comprehensive process integration and cannot realize unified management and control of financial information [11]. Conventional financial management frameworks are increasingly ill-suited to address the sector's need for timely data processing, precise cost accounting, and accurate market forecasting, leaving firms vulnerable to the industry's complex and dynamic environment.

Rapid advancements in AI, particularly in machine learning, data analytics, and natural language processing, offer promising avenues for addressing these challenges [12]. Intelligent financial management systems designed around a three-tier “data–algorithm–application” architecture have emerged as a viable solution [13]. At the data layer, robotic process automation (RPA) and API (Application Programming Interface)-based integrations facilitate automated acquisition and consolidation of heterogeneous data from supply chain operations, omnichannel sales, and inventory management, effectively breaking down data silos and enhancing data accessibility [14]. At the algorithm layer, advanced machine learning and deep learning models are utilized: long short-term memory (LSTM) networks enable forecasting of raw material price trends, while intelligent cost-allocation models optimize complex cost accounting procedures, effectively addressing cost control challenges [15,16]. At the application layer, algorithmic outputs are transformed into actionable management modules: an intelligent budgeting module supports dynamic budget formulation and real-time monitoring [17]; a smart risk-control module leverages predefined performance indicators to provide early warnings for inventory overstock and cash flow disruptions [18]; and a decision-support module integrates multidimensional data and visualization analytics to deliver data-driven insights for strategic decisions, such as pricing and market expansion [19]. By deploying these intelligent models, AI systems enable comprehensive, fine-grained tracking of every stage of the value chain—from raw material procurement to production and distribution—substantially improving cost-accounting accuracy and upgrading financial management from a retrospective accounting approach to an integrated paradigm of predictive, real-time, and post-hoc analytical control.

A considerable body of scholarship has examined intelligent finance and the digital transformation of the textile and apparel sector. Existing research can be broadly categorized into two strands. The first strand explores the conceptual underpinnings and architectural frameworks of intelligent finance, underscoring the pivotal role of information technologies and AI in enhancing financial management efficiency. For example, deep-learning-based models have been proposed to improve the reliability of retail financial management [20], while studies utilizing variational autoencoders (VAEs) have demonstrated enhanced predictive capacity in enterprise financial risk assessment [21]. These contributions have laid critical theoretical and technical foundations for the advancement of intelligent financial systems. The second strand of research focuses on the unique challenges encountered by textile and apparel enterprises during digital transformation, with studies primarily analyzing the effects of digitalization on accounting practices in small and medium-sized enterprises and proposing transformation pathways across the technological, personnel, and organizational dimensions [22,23]. Further investigations have examined the implementation of enterprise resource planning (ERP) systems to enhance managerial effectiveness in textile firms and the evolving requirements for financial management in the digital era [24,25].

Despite the aforementioned advances, significant gaps persist. The majority of the extant literature has concentrated on generic corporate financial management frameworks and overlooked the end-to-end characteristics of the textile and apparel value chain—from fabric procurement to finished-garment sales. For example, only a few studies have quantified the financial implications of capital tied up in lengthy procurement cycles or the write-down risks associated with fast-fashion inventory. Moreover, many prior studies have been primarily theoretical or relied on model-based approaches predicated on idealized assumptions, insufficiently accounting for real-world complexities, such as inconsistent data quality and the challenges of multi-source data integration. Longitudinal and comparative evaluations of AI-based financial management systems within textile and apparel enterprises remain scarce, leaving the empirical evidence of their performance impact in key areas—cost control, risk forecasting, and strategic decision support—generally inconclusive. To fill in this gap, the present study conducts a comparative assessment of operational data from textile and apparel enterprises that have adopted AI-driven financial management systems and those that have not, thereby providing a rigorous evaluation of the net performance effects of these systems.

METHODS

Research Design

This study adopts a quasi-experimental design utilizing propensity score matching (PSM) to construct comparable treatment and control groups. The observation group comprises textile and apparel enterprises that have implemented AI-based financial management systems, while the control group includes comparable firms without such systems. Quantitative comparisons of financial and operational metrics across both groups over a defined period are complemented by in-depth case studies of representative firms. This mixed-methods approach is intended to control for confounding influences and provide a rigorous estimation of the net performance effects of AI-enabled financial management.

Sample Selection and Matching

A preliminary pool of approximately 200 textile and apparel enterprises operating in China's Yangtze River Delta and Pearl River Delta regions was identified through industry associations, public databases, and collaborative partners. All firms share comparable core operations, including apparel production, sales, and textile raw material procurement. To mitigate self-selection bias, PSM was applied with AI financial management system adoption coded as a binary treatment variable (1 = adopter; 0 = non-adopter). Covariates included total assets, annual revenue, number of employees, firm age, debt-to-asset ratio (DAR), proportion of online sales, and R&D intensity. Logistic regression estimates were used to generate propensity scores, and 1:1 nearest-neighbor matching with a caliper of 0.02 was implemented. The final matched sample comprised 60 enterprises—30 treatment and 30 control. Post-matching diagnostics confirmed satisfactory covariate balance, with standardized biases below 10% and non-significant t-tests ($p > 0.1$), indicating comparability between groups on observed characteristics.

Data Collection and Measures

Data Sources

Financial data were primarily obtained from the CSMAR and Wind databases (for listed firms) and validated against audited annual reports. Additional data were collected through standardized survey instruments and, where applicable, on-site interviews and internal system log reviews. Interviewees included chief financial officers (CFOs), senior financial managers, and frontline accounting staff.

Key Measures

Profitability: Gross profit margin (GPM) and net profit margin (NPM)

Solvency: DAR

Procurement Cost Savings Rate: Percentage savings relative to contemporaneous market benchmarks, calculated as follows:

$$\frac{Market\ Benchmark\ Total\ Cost - Actual\ Procurement\ Total\ Cost}{Market\ Benchmark\ Total\ Cost} \times 100\%$$

Inventory Obsolescence Rate: Proportion of inventory value comprising items held for over 180 days at quarter-end.

Financial Process Automation Rate: Share of accounting transactions processed automatically without human intervention based on system log analysis.

Budget Execution Deviation Rate (BEDR): Percentage deviation of actual revenue and expenditure from budgeted figures.

Analytical Strategy

Quantitative analyses were conducted using SPSS 25.0, with independent samples t-tests utilized to assess group differences in key performance measures at a significance level of $p < 0.05$. To provide explanatory depth, two firms from the observation group and one from the control group were selected for qualitative case studies. Interview transcripts, meeting minutes, and internal documentation were coded and analyzed using process tracing to elucidate the mechanisms through which AI-enabled systems influence managerial decision-making, particularly with respect to budgetary accuracy. Qualitative findings were triangulated with quantitative results to enhance the robustness of interpretations presented in the Discussion section.

RESULTS AND DISCUSSION

Impact on Key Financial Ratios

Table 1 presents statistically significant differences in key financial indicators between the treatment and control groups. Firms utilizing AI-based financial management systems exhibited superior profitability, with GPM and NPM averaging 36.5% and 20.2%, respectively, compared with 28.1% and 12.5%, respectively, for non-adopters ($p < 0.001$). In addition, the observation group demonstrated a notably stronger capital structure, reflected in a significantly lower DAR of 41.7% versus 55.9% in the control group.

These results suggest that AI-enabled financial management systems contribute to enhanced profitability by enabling data-driven optimization of cost control and pricing strategies. Leveraging predictive analytics for raw material price fluctuations and process optimization, the system effectively reduces unit costs [26]. Furthermore, real-time cash flow monitoring and forecasting facilitate prudent debt management, enabling firms to maintain considerably healthy leverage ratios and mitigate financial risk, thereby strengthening overall capital structure.

Table 1. Comparison of key financial ratios between the treatment and control groups

Indicators	Observation group (n = 30)	Control group (n = 30)	t-values	p-values
Gross Profit Margin (%)	36.5 ± 3.1	28.1 ± 2.6	10.51	<0.001
Net Profit Margin (%)	20.2 ± 1.7	12.5 ± 1.5	17.98	<0.001
Debt-to-Asset Ratio (%)	41.7 ± 6.3	55.9 ± 6.2	-8.92	<0.001

Impact on Profitability

Figure 1 compares three-year averages of operating revenue and costs across the matched groups. AI-adopting firms reported significantly high revenues (CNY 490 million vs. CNY 410 million) while limiting cost growth (CNY 310 million), indicating revenue expansion and also quality-driven growth [27]. The system's predictive analytics in market trends and demand, coupled with granular supply chain cost control—from supplier negotiations to energy optimization and inventory turnover—delivered a marked profitability edge over non-adopters.

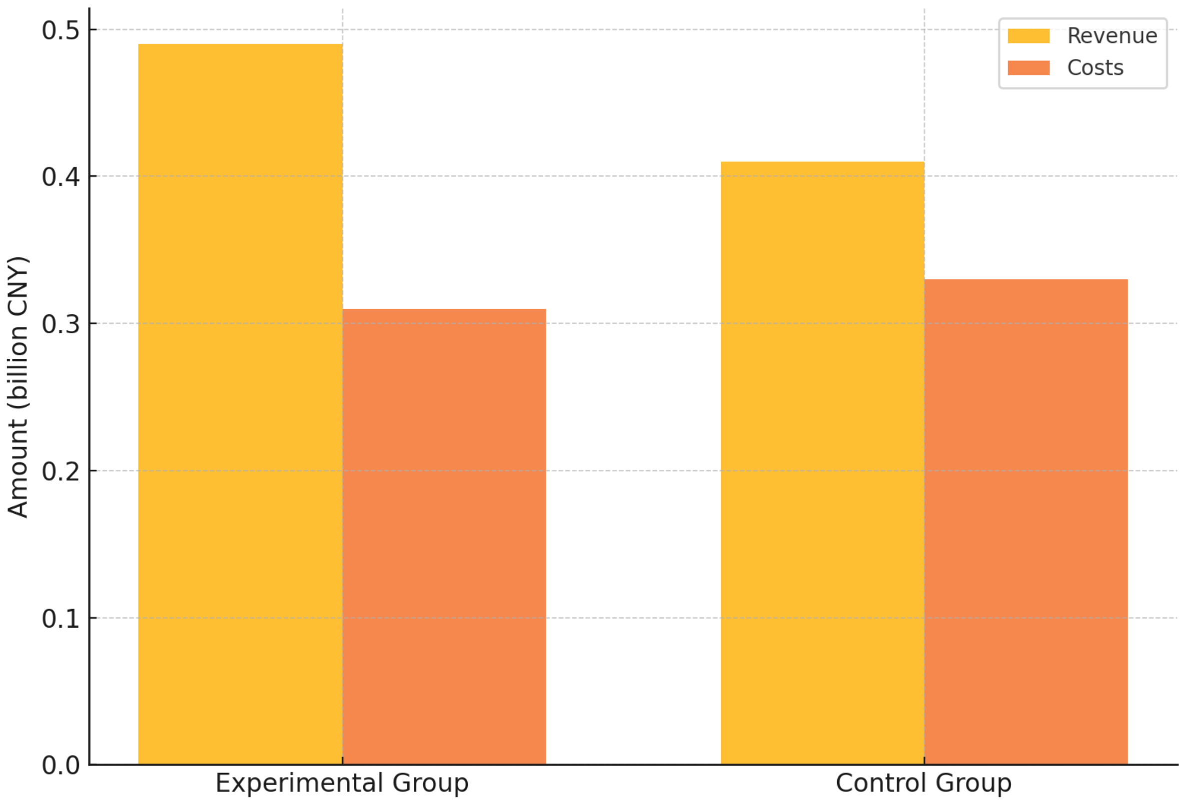

Figure 1. Comparison of Profitability: Experimental Group vs Control Group

Impact on Capital Structure and Solvency

Figure 2 highlights differences in capital structure. Total assets did not significantly differ between groups ($p > 0.05$), excluding scale effects. However, AI adopters exhibited substantially low short-term liabilities (CNY 140 million vs. CNY 240 million) and a markedly balanced debt profile. These results indicate that solvency gains stem from structural optimization rather than asset expansion. Leveraging intelligent cash flow forecasting and risk alerts, AI systems minimize reliance on short-term borrowing and enable access to stable long-term financing, thereby alleviating repayment pressure and liquidity risk [28].

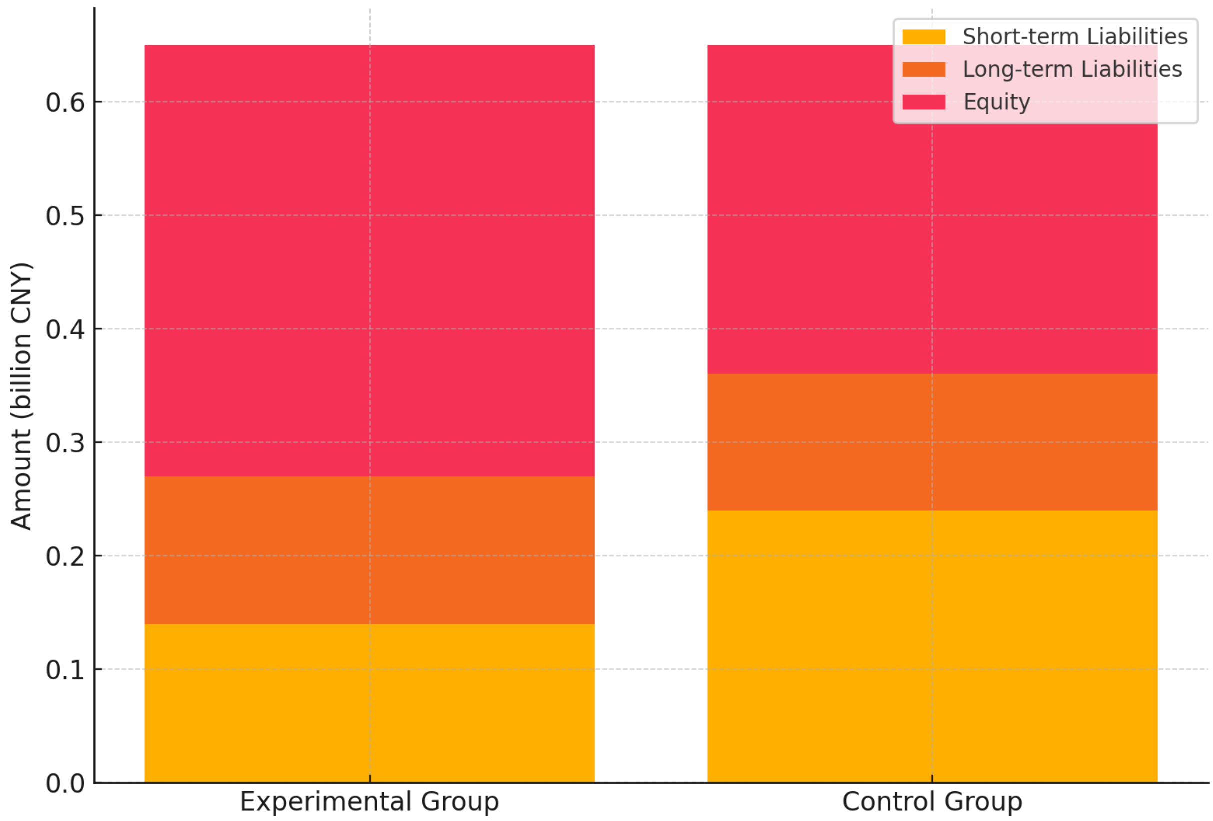

Figure 2. Comparison of Asset–Liability Structure: Experimental Group vs. Control Group

Impact on Operational Efficiency

Three key efficiency indicators (Table 2) demonstrate a consistent advantage for AI-enabled firms: procurement cost savings averaged 16.5%, inventory obsolescence decreased to 8.9%, and financial process automation reached 75.8%. Case evidence illustrates the mechanisms: a fast-fashion CFO noted, "*Over 70% of voucher generation and reconciliation are now automated, allowing our team to focus on cost-benefit analyses for sales decisions.*" By contrast, a control group manager admitted, "*Cost anomalies are often discovered two weeks late, delaying corrective action.*" These findings confirm that automation and data-driven optimization directly translate into operational performance gains.

Table 2. Comparison of key operational efficiency indicators between the treatment and control groups

Indicators	Observation group (n = 30)	Control group (n = 30)	t-values	p-values
Procurement cost savings rate (%)	16.5 ± 4.2	2.1 ± 1.5	16.25	<0.001
Inventory obsolescence rate (%)	8.9 ± 3.5	25.4 ± 6.8	−12.11	<0.001
Financial process automation rate (%)	75.8 ± 10.1	12.3 ± 5.5	28.93	<0.001

Impact on Decision Quality

Figure 3 shows significantly low budget deviation rates for AI adopters in revenue and costs, underscoring the effectiveness of AI-enabled dynamic budgeting. By continuously tracking variances and issuing predictive alerts, the system embeds foresight into managerial decision-making. Process-tracing revealed a shift from retrospective diagnosis to proactive intervention: one firm preemptively mitigated an anticipated 8% labor cost overrun in its Vietnam plant by immediately activating alternative supplier inquiries. Such predictive capabilities demonstrably enhance budgetary accuracy and decision timeliness.

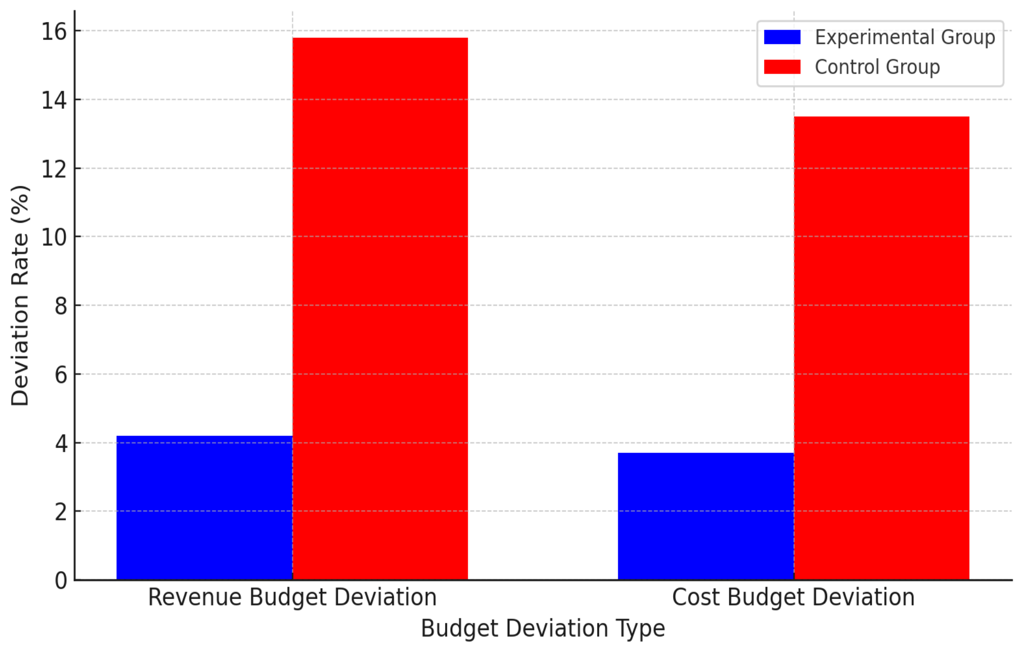

Figure 3. Comparison of Budget Execution Deviation: Experimental Group vs. Control Group

CONCLUSION

By using PSM and a mixed-methods design, this study rigorously evaluated the effects of AI-enabled financial management systems in 60 textile and apparel enterprises. Evidence demonstrates that AI adoption significantly improves financial outcomes and also reshapes firms' operational efficiency and decision-making dynamics. AI systems, compared with traditional approaches, elevated gross and net profit margins through granular cost control and dynamic pricing, while strengthening solvency by optimizing debt structures and reducing reliance on short-term liabilities.

Operational benefits were equally pronounced. AI adopters achieved average procurement cost savings exceeding 15%, reduced inventory obsolescence to approximately one-third of that in non-adopters, and reached automation rates of 75% in financial processes. These improvements enhanced accounting efficiency and accuracy while freeing finance teams to focus on strategic analysis. Moreover, dynamic budgeting and predictive analytics reduced budget deviation rates, fostering a proactive, intervention-oriented decision culture. Qualitative case evidence highlighted the underlying mechanisms, showing how AI systems become embedded in management routines and shift decision-making from ex post diagnostics to ex ante control.

By combining PSM-based causal inference with complementary qualitative insights, this research provides robust empirical support for AI's transformative value in financial management, addressing a literature gap dominated by theoretical models or studies lacking rigorous identification. Methodologically, the mixed-methods approach offers a replicable framework for assessing AI applications in other traditional manufacturing sectors. Managerially, the findings underscore that AI financial systems should be viewed not as IT expenditures but as strategic investments capable of driving sustainable growth, optimizing capital structures, and enhancing decision quality. However, successful implementation requires complementary data governance frameworks and the upskilling of financial personnel to assume new roles in analytics-driven strategic support.

Limitations likewise remain in this study. Despite rigorous matching, the sample is restricted to firms of particular sizes and regions in China, thereby limiting generalizability. The three-year observation window determines the operational effects but may not fully reflect long-term strategic, brand, or competitive impact. Furthermore, unobserved factors, such as entrepreneurial orientation and organizational learning capacity, may still influence outcomes. Future research should pursue (i) large-scale, cross-regional studies to strengthen external validity; (ii) longitudinal designs to assess long-term consequences; (iii) advanced econometric techniques, including instrumental variables or difference-in-differences models, to address endogeneity; and (iv) extensive exploration of the "soft" challenges of AI adoption, including data governance, organizational ethics, and workforce transformation.

Author Contributions

Min Zhang and Min Huang designed the study; all authors conducted the study; Min Zhang and Min Huang collected and analyzed the data. Min Huang and Min Zhang participated in drafting the manuscript, and all authors contributed to critical revision of the manuscript for important intellectual content. All authors gave final approval of the version to be published. All authors participated fully in the work, took public responsibility for appropriate portions of the content, and agreed to be accountable for all aspects of the work in ensuring that questions related to the accuracy or completeness of any part of the work were appropriately investigated and resolved.

Conflict of Interest

The authors declare no conflict of interest.

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Ethics Approval and Consent to Participate

This study was approved by the Ethics Committee of Nanning Normal University. The research has been authorized by the company and the informed consent of the personnel involved in the questionnaire survey has also been obtained, and responses were collected anonymously. No personally identifiable information was stored.

Availability of Data and Materials

The datasets used and/or analysed during the current study were available from the corresponding author on reasonable request.

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Not applicable.

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