Differences in Financial Performance of Firms with Established Controlling Depending on the Use of AI

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This paper examines the relationship between the use of artificial intelligence (AI) and the economic performance of firms with an established controlling system. The aim of the study is to assess empirically whether accounting and financial indicators differ significantly between firms that use artificial intelligence and those that do not. The research sample consists of firms with established controlling, which are divided into two groups based on their use of artificial intelligence tools. The analysis draws on accounting data and selected indicators capturing cost structure, liquidity-related asset structure and short-term financial position, as well as operating performance and cash conversion efficiency. Given the nature of the data, the nonparametric Mann-Whitney U test is employed to test for differences between the two groups. The results contribute to the ongoing discussion on the role of artificial intelligence in corporate management and controlling by providing empirical evidence on whether AI use is associated with firms' economic outcomes.

Keywords:
Artificial Intelligence,
Management control systems,
Cost structure,
Liquidity and asset structure,
Mann-Whitney U Test

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1 Introduction

Digital transformation is reshaping how firms create value, organize work, and make decisions. The literature commonly views it as a gradual process in which digital technologies create disruptions, trigger strategic responses, and lead to changes in value creation and organizational structures (Vial, 2019; Verhoef et al., 2021). Recent reviews also stress that performance outcomes depend on the interaction between technology and organizational change - digital tools rarely improve results on their own, but rather through how they are embedded in routines, capabilities, and control systems (Plekhanov et al., 2023; Volberda et al., 2021).

Within this broader shift, artificial intelligence (AI) is particularly important because it supports both automation and more advanced, data-driven decision support. This is often described as an "automation–augmentation" tension, where AI can replace some tasks while strengthening human judgment in others (Raisch & Krakowski, 2021). In accounting and controlling, this raises a practical and research-relevant question: whether AI use is linked to measurable differences in firm outcomes, especially in organizations that already rely on planning, performance measurement, and variance-based steering.

Research on management accounting and AI is increasingly moving from conceptual discussions to studies that connect AI-related practices with organizational consequences, but empirical evidence remains uneven across settings and outcomes (Abbas, 2025; Stratopoulos & Wang, 2025). In addition, the expected benefits of AI in finance and controlling are likely to depend on enabling conditions such as data quality and availability, governance arrangements, employee skills, and alignment with finance objectives (Bedford et al., 2025; Steens et al., 2024). These considerations motivate an empirical comparison of firms with similar management control conditions that differ in their use of AI elements.

The objective of this paper is to examine empirically whether firms with an established controlling function differ in accounting-based indicators depending on whether they report using AI-related elements. The analysis focuses on three domains observable from financial statements: (i) cost structure, (ii) liquidity-related asset structure and short-term financial position, and (iii) operating performance and cash conversion efficiency. Differences between AI-using and non-using firms are assessed using the Mann-Whitney U test. To achieve this objective, the study addresses the following research questions focusing on differences within the controlling-implemented subsample:

RQ1: Do AI-using and non-using controlling firms differ in cost structure?
RQ2: Do AI-using and non-using controlling firms differ in liquidity-related asset structure and short-term financial position?
RQ3: Do AI-using and non-using controlling firms differ in operating performance and cash conversion efficiency?

2 Literature review

2.1 The Influence of Capabilities and Management Control on Digital Transformation Outcomes and AI Adoption

Recent digital transformation research consistently shows that performance outcomes depend less on adoption itself and more on how digital technologies interact with organizational arrangements. Digital transformation is commonly described as a process in which technologies create disruptions that trigger strategic responses, while outcomes are shaped by organizational barriers and structural change (Vial, 2019). It also requires coordinated adjustments in strategy, structure, processes, and customer-facing activities, which makes internal governance and decision infrastructures critical boundary conditions (Verhoef et al., 2021). Review studies further emphasize that the field increasingly focuses on how firms overcome cognitive barriers, redesign routines, and develop new organizational forms, reinforcing the role of managerial systems and controls in converting digital initiatives into performance improvements (Plekhanov et al., 2023; Volberda et al., 2021).

From a controlling perspective, these arguments are particularly relevant because controlling can be understood as a formal infrastructure for steering organizations through planning, performance measurement, and variance-based feedback. In this sense, management control systems (MCS) are not merely supportive tools but complementary mechanisms that influence how digital technologies are selected, implemented, and used. Empirical evidence from SMEs suggests that digitalization is associated with the maturity of management control practices and that the realized benefits depend on organizational conditions that shape this relationship (Broccardo et al., 2024). Conceptual work on management control combinations likewise calls for closer attention to the mechanisms through which sets of controls emerge and affect outcomes - an issue that becomes more salient as digital technologies increase data granularity, timeliness, and the pace of decision cycles (Bedford, 2020).

AI differs from earlier waves of digitalization because it can automate tasks while also augmenting managerial judgment through predictive and generative capabilities. The automation–augmentation paradox highlights that AI may improve efficiency in some areas while creating new coordination and governance challenges, including overreliance and accountability concerns (Raisch & Krakowski, 2021). Studies on AI for decision-making emphasize that value depends on integrating AI outputs into decision processes, maintaining data quality, and aligning AI use with managerial information needs (Duan et al., 2019). A capability-based view has therefore become central to explaining why AI outcomes vary across firms: AI capability is typically defined as a configuration of resources and routines that enables effective deployment and is empirically linked to performance outcomes (Mikalef & Gupta, 2021). Related evidence in information systems reports a similar association, while stressing that effects depend on complementary organizational conditions and the broader digital context (Fosso Wamba et al., 2024). Financial economics research also suggests that AI investment is associated with higher firm growth and valuation, with growth largely driven by product innovation, which supports the idea that AI can reshape competitive dynamics through capability development (Babina et al., 2024).

2.2 Digitalization in Finance and Controlling and the Accounting Visibility of AI Effects

Digital transformation increasingly unfolds within the finance function, where automation and analytics reshape both routine work and the advisory role of controllers. However, the uptake of these tools is uneven and tends to reflect a firm's broader digital strategy as well as the orientation of the finance function toward efficiency gains versus business partnering (Bedford et al., 2025). Management accounting research therefore cautions against treating digitalization as a simple, linear change with direct performance effects. Digital data environments alter practices because data become more granular, abundant, and machine-processable

(Bhimani, 2020), and they can also influence organizational boundaries, power relations, and the ways in which accounting knowledge is produced (Knudsen, 2020). Recent evidence further suggests that the ability to benefit from analytics and AI depends on competencies, as controllers increasingly require digital skills and structured competence development (Steens et al., 2024). Field-based insights from forecasting and analytics projects similarly indicate that benefits often emerge through staged implementation rather than immediate large-scale transformation (Schnegg & Möller, 2022). Taken together, these studies imply that AI value in controlling is typically conditional on organizational embedding, governance, and skills, rather than on adoption alone.

Against this backdrop, accounting-based indicators offer a practical lens for examining whether AI-enabled controlling is associated with observable differences in firm outcomes. Recent syntheses map the intersection of AI and management accounting and call for empirical work that links AI-enabled practices to organizational consequences (Abbas, 2025; Stratopoulos & Wang, 2025). Research also highlights that firms often scale simpler AI applications more widely than complex tools and face persistent challenges related to explainability, bias, privacy, robustness, and overreliance (Kokina et al., 2025). Evidence on automation likewise shows that implementation outcomes depend on process clarity, governance, and careful human–machine design (Perdana et al., 2023), while broader assessments point to ongoing pressures on accounting professions to adopt new methods and competencies (Tiberius & Hirth, 2019). These insights converge on a key implication: observable performance differences between AI-using and non-using firms are most likely when AI is integrated into routines supported by appropriate capabilities and governance.

Overall, the literature suggests that AI embedded in finance and controlling routines has the potential to enhance decision quality, forecasting, reporting, and operational efficiency. However, these benefits are unlikely to arise from technology adoption alone. They depend on data quality, digital competencies, governance arrangements, and the extent to which AI outputs are integrated into managerial decision-making processes. Accounting-based indicators therefore provide a useful, although necessarily limited, lens for examining whether AI use is associated with observable differences in firm outcomes. In response to recent calls for empirical research linking AI-related practices to organizational consequences, this study compares firms with established controlling that differ in reported AI use and examines whether these differences are reflected in selected financial-statement indicators.

3 Methodology

This research combines questionnaire-based primary data with secondary accounting and financial statement data. The primary data come from a questionnaire survey capturing firm practices and managerial approaches, including whether the firm has implemented controlling and whether it uses AI-related elements. In addition, secondary accounting and financial statement data were used. These financial data were obtained from the Albertina Gold Edition database and matched to the survey responses at the firm level.

In total, 201 valid questionnaire responses were collected. Among the participating firms, 74 reported that controlling is implemented, while 127 reported that controlling is not implemented or that they only use basic cost accounting tools. The conference analysis focuses on the subsample of firms with controlling implemented. This subsample initially included 74 firms, but after data cleaning and the matching of survey responses with financial statement records, the final analytical sample consisted of 64 firms. Within this final sample, firms were classified according to reported AI use: 41 firms were categorized as AI-using firms, and 23 firms as non-AI firms. AI use is measured in this study as a binary variable. Firms were classified as AI-using firms if they reported the use of AI-related elements, and as non-AI firms if they did not report such use. This operationalization is suitable for an initial exploratory comparison because it enables the analysis to identify whether the presence of reported AI use is associated with differences in accounting-based indicators within firms that already have controlling implemented. However, the measure does not capture the intensity, maturity, functional scope, or specific type of AI application. Firms classified as AI-using firms may therefore differ in the extent to which AI is embedded in controlling processes, financial planning, reporting, forecasting, or managerial decision support. For this reason, the results should be interpreted as evidence of differences associated with reported AI use rather than as evidence of the effects of advanced or fully integrated AI-based controlling systems. Future research should develop more granular measures of AI adoption, for example by distinguishing between basic automation, predictive analytics, generative AI applications, decision-support systems, and strategically integrated AI-based controlling solutions. All statistical tests and comparisons reported in this paper are therefore based on this cleaned and matched subsample (N = 64).

The study uses six accounting-based indicators, grouped into three domains. The first domain captures cost structure through the administrative cost ratio and the personnel cost ratio, reflecting both potential short-term implementation costs and process-related efficiency effects. The second domain focuses on liquidity-related balance-sheet characteristics, measured by financial assets as a share of total assets and the cash ratio, which together describe the firm's liquid asset position and short-term financial buffer. The third domain captures operating performance and cash conversion, using operating profit margin and days sales outstanding (DSO), to assess whether differences in cost structure and liquidity management are reflected in operating outcomes and receivables collection efficiency. The six indicators are organized as follows:

Group 1: Cost structure and cost discipline

1. Administrative cost ratio (Administrative and other expenses / Operating revenues)
2. Personnel cost ratio (Personnel expenses / Operating revenues)

Group 2: Liquidity-related asset structure and short-term financial position

3. Financial assets as % of total assets
4. Cash ratio (immediate liquidity)

Group 3: Operating performance and cash conversion

5. Operating profit margin (Operating profit / Operating revenues)
6. Days sales outstanding (DSO) (Days receivables turnover)

Statistical methods

Testing for normality of data distribution

Prior to the empirical analysis, the distributional properties of the analysed financial indicators were examined to inform the choice of appropriate statistical methods. Testing for normality represents a standard procedure in empirical research based on accounting data, particularly in comparative studies. The variables were assessed using the Shapiro-Wilk test, which is commonly applied in empirical accounting and financial research (Shapiro & Wilk, 1965; Field, 2018).

The results indicate that a considerable proportion of the analysed indicators deviates from a normal distribution. Such distributional patterns are typical for accounting-based financial data, which are frequently affected by skewness and extreme values. Given the violation of the normality assumption, the application of parametric statistical methods was deemed inappropriate, and the subsequent analysis therefore relies on non-parametric techniques.

Testing of relationships by Mann-Whitney U test

The Mann-Whitney U test was used to examine differences in financial characteristics between AI-using and non-AI firms with implemented controlling. This non-parametric test is suitable for comparing two independent samples when the assumption of normality is violated (Nachar, 2008; Devore, 2015).

The Mann-Whitney U test evaluates whether the distributions of a given financial indicator differ between the two groups. The test was applied separately to each financial indicator to assess whether statistically significant differences exist between firms. Although the sample sizes differ between the groups, the Mann-Whitney U test remains appropriate, as it is robust to unequal group sizes and does not rely on distributional assumptions.

All tests were evaluated at a significance level of $\alpha = 0.05$. This approach is consistent with the formulated research questions.

4 Results

4.1 Testing for Normality of Data Distribution

Prior to hypothesis testing, the distributional properties of the analysed variables were examined to determine the suitability of subsequent statistical procedures. The normality of the data and the distribution of the sample were assessed using the Shapiro-Wilk test, which is widely recommended for evaluating normality in empirical research (Shapiro & Wilk, 1965; Field, 2018).

The results of the Shapiro-Wilk test indicated that the assumption of normal distribution could not be confirmed for a substantial part of the analysed financial indicators. This finding is consistent with the characteristics of accounting and financial data. Consequently, the subsequent analysis relied on non-parametric statistical methods that do not require normality of the data and are robust to deviations from standard distributional assumptions.

4.2 Mann-Whitney U test

Differences between AI-using and non-using firms were assessed using the Mann–Whitney U test, which is suitable for financial statement indicators that are typically non-normally distributed and may include outliers. The test evaluates whether the distributions of an indicator differ between two independent groups by comparing rank positions rather than raw values. In Table 1, "Sum (NO)" and "Sum (YES)" represent the sums of ranks for the non-AI and AI groups, respectivelyHigher mean ranks indicate higher typical values of the indicator in the respective group. Because not all firms had complete information for every indicator, the number of observations differs slightly across indicators.

Table 1: Mann-Whitney U Test Results for Differences in Accounting-Based Indicators Between AI-Using and Non-AI Firms

Financial Indicator	Sum (NO)	Sum (YES)	U	Z	p-value
Administrative cost ratio	415	1016	205	-2.284	0.022
Personnel cost ratio	544	887	326	0.064	0.948
Financial assets as % of assets	650	781	220	2.009	0.044
Cash ratio	579	799	271	0.912	0.361
Operating profit margin	507	924	297	-0.596	0.550
DSO	573.5	857.5	296.5	0.605	0.544

Source: own processing

Group 1: Cost structure and cost discipline

The first group includes the administrative cost ratio and the personnel cost ratio, both expressed relative to operating revenues. The administrative cost ratio exhibits a statistically significant difference between AI-using firms and non-AI firms ($U = 205$; $Z = -2.284$; $p = 0.022$). The rank distribution indicates higher values among AI-using firms, as reflected by a markedly larger rank sum in the AI group (Sum(YES) = 1016) compared to the non-AI group (Sum(NO) = 415). In substantive terms, this suggests that firms reporting AI use tend to show a higher administrative cost burden relative to operating revenues. The differences are shown in Figure 1.

By contrast, the personnel cost ratio does not differ between the groups ($U = 326$; $Z = 0.064$; $p = 0.948$). Rank sums are nearly identical in relative terms, indicating that labor cost intensity does not distinguish AI-using firms from non-using firms in this dataset. Taken together, these results suggest that group differences within the cost structure domain are concentrated in administrative and related overhead-type expenditures rather than in personnel cost intensity.

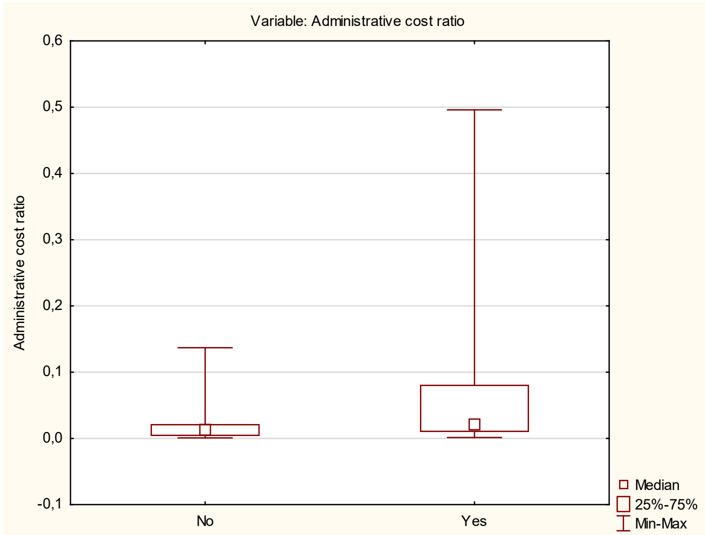

Figure 1: Mann-Whitney U Test - Administrative Cost Ratio
Source: own processing

Group 2: Liquidity-related asset structure and short-term financial position

The second group includes financial assets as a percentage of total assets and the cash ratio, which together capture liquidity-related asset structure and the short-term financial position. Financial assets as a percentage of assets shows a statistically significant difference between the groups (U = 220; Z = 2.009; p = 0.044). Here, the rank pattern indicates that non-AI firms tend to have higher values of this indicator (Sum(NO) = 650) than AI-using firms (Sum(YES) = 781), implying a higher relative allocation to financial assets among non-AI firms. The differences are shown in Figure 2.

The cash ratio, however, does not show a statistically significant difference (U = 271; Z = 0.912; p = 0.361). Although the ranks suggest a tendency toward higher immediate liquidity among non-AI firms, the observed difference is not sufficiently consistent to be statistically supported in this sample. Overall, the results in this group indicate that the most robust distinction concerns the composition of assets rather than cash holdings alone.

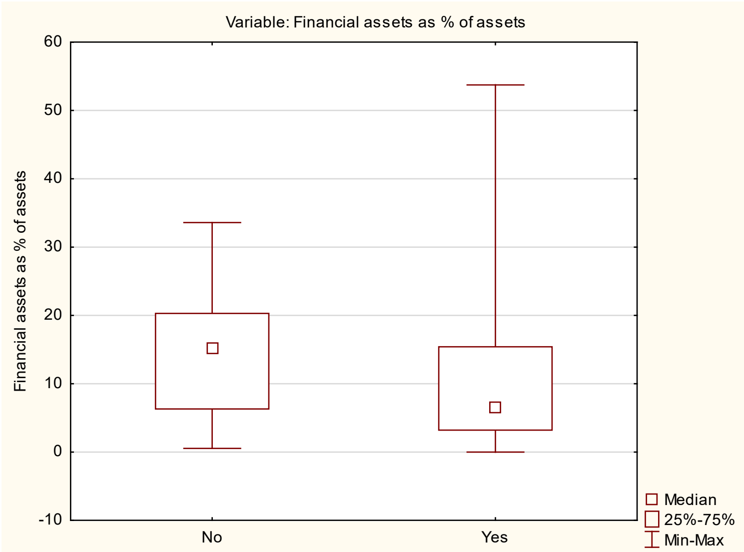

Figure 2: Mann-Whitney U Test - Financial Assets as % of Assets
Source: own processing

Group 3: Operating performance and cash conversion

The third group focuses on operating profit margin and days sales outstanding (DSO) as a proxy for receivables conversion. Neither indicator displays a statistically significant difference between AI-using firms and non-AI firms. Operating profit margin yields $U = 297$ ($Z = -0.596$; $p = 0.550$), while DSO yields $U = 296.5$ ($Z = 0.605$; $p = 0.544$). The direction of rank differences is modest and inconsistent, indicating that AI use is not associated with observable differences in operating profitability or receivables turnover.

Across the six indicators, statistically significant differences are detected for two measures: the administrative cost ratio (higher among AI-using firms) and financial assets as a share of total assets (higher among non-AI firms). The remaining indicators (personnel cost ratio, cash ratio, operating profit margin, and DSO) do not exhibit statistically supported differences between the groups.

5 Discussion

The observed pattern is consistent with a scenario in which AI adoption within firms that already have established controlling is reflected initially in organizational and structural adjustments rather than in immediate improvements in traditional performance metrics. The higher administrative cost ratio among AI-using firms may indicate early-stage investments and operating expenses associated with AI-related implementation, integration, data governance, external services, training, and the development of analytical support routines. This interpretation is consistent with the automation–augmentation perspective, which suggests that AI adoption often brings additional coordination, governance, and accountability demands that can increase overhead-type costs, particularly in the early stages of implementation (Raisch & Krakowski, 2021). These costs can be visible sooner than any resulting productivity or profitability gains, which may require more time to materialize and may depend on the depth and scope of AI use. In line with digital transformation research, performance improvements typically materialize only when technological adoption is complemented by process redesign and organizational change, which implies that short-term accounting effects may be weak even when implementation activity is substantial (Vial, 2019; Verhoef et al., 2021).

The finding that non-AI firms exhibit a higher share of financial assets in total assets suggests a difference in balance-sheet composition and potentially in liquidity-buffer strategies or capital allocation preferences. Such a pattern resonates with capability-based arguments that AI-related value creation often requires resource reallocation toward data, systems, and complementary routines, which may temporarily reduce the relative weight of liquid financial assets on the balance sheet (Mikalef & Gupta, 2021). One plausible interpretation is that AI-using firms allocate relatively less of their asset base to financial instruments, possibly because resources are directed toward operating assets, process reconfiguration, or digital capability building. Related evidence from financial economics links AI investment to firm growth and innovation outcomes (Babina et al., 2024), which is compatible with the notion that firms pursuing AI may prioritize capability-building investments over holding a larger share of financial assets. At the same time, the absence of statistically significant differences in operating profit margin and DSO implies that, in this dataset, AI use does not translate into immediately observable advantages in operating profitability or receivables conversion. This reinforces the notion that the short-term effects of AI adoption may be complex and may involve trade-offs, such as higher administrative costs in exchange for capabilities that could yield benefits over a longer horizon.

At the same time, the results should be interpreted with caution with respect to causality. The empirical design identifies statistically significant differences between AI-using and non-using firms, but it does not allow a causal conclusion that AI use directly caused the observed differences in administrative cost intensity or asset structure. It is also possible that firms with specific organizational characteristics, higher managerial sophistication, stronger digital orientation, or different investment priorities are more likely to adopt AI in the first place. In this sense, AI use may be both a potential driver of financial and organizational change and an indicator of broader transformation processes already taking place within the firm. The findings therefore demonstrate association rather than causation. Establishing causal effects would require longitudinal data, more detailed information on the timing and intensity of AI implementation, and additional controls for firm size, sector, digital maturity, and strategic orientation.

These results provide a coherent narrative: within controlling-enabled firms, AI use appears more strongly associated with differences in administrative cost intensity and asset-structure characteristics than with short-term operating performance. This supports the view that early-stage AI adoption may be reflected in the cost base and balance-sheet configuration before it is reflected in conventional profitability or working-capital outcomes.

The findings also provide practical implications for managers and controllers. For practitioners implementing AI in controlling, the results suggest that AI adoption should not be assessed only through immediate improvements in profitability or working-capital efficiency. In the early stages, AI use may be associated with higher administrative costs due to system integration, data preparation, process redesign, employee training, external services, and governance requirements. Controllers should therefore distinguish between short-term implementation costs and potential long-term benefits, such as faster reporting, improved forecasting, better analytical support, and more timely managerial information. Managers should also ensure that AI tools are embedded into existing controlling routines and supported by clear responsibilities, data quality management, and evaluation criteria. The absence of

significant differences in operating profit margin and DSO further indicates that AI adoption alone does not automatically lead to superior financial performance; its benefits depend on how effectively it is integrated into decision-making and organizational processes.
Finally, the findings speak directly to recent calls in the accounting and management accounting literature for empirically linking AI-related adoption to observable firm outcomes using financial statement data, including the documentation of non-effects and early-stage cost patterns (Abbas, 2025; Stratopoulos & Wang, 2025).

6 Conclusion

This paper examined whether firms with established controlling differ in selected accounting-based indicators depending on whether they report using AI-related elements. Across the six indicators grouped into cost structure, liquidity-related asset structure, and operating performance/cash conversion, statistically significant differences were observed for two measures. First, AI-using firms exhibited a higher administrative cost ratio, suggesting that AI adoption is associated with a higher administrative cost burden relative to operating revenues in the short run. Second, non-AI firms showed a higher share of financial assets in total assets, indicating differences in balance-sheet composition and potentially in liquidity-buffer strategies or capital allocation preferences. In contrast, personnel cost ratio, cash ratio, operating profit margin, and days sales outstanding did not show statistically supported differences between AI-using firms and non-AI firms.

This contributes evidence that early-stage AI adoption may involve observable organizational and financial-structural adjustments, while performance effects in core profitability or working-capital metrics may require longer observation windows, more granular measures of AI intensity, or additional controls for firm heterogeneity.

This study has several limitations. First, the final analytical sample is relatively modest, which limits the generalizability of the findings and reduces the statistical power of the analysis. Second, the study is based on cross-sectional data, and therefore it does not allow causal inference. The observed differences should be interpreted as associations between reported AI use and selected accounting-based indicators, not as proof that AI adoption directly caused these differences. Third, AI use is measured as a binary variable, which does not capture the intensity, maturity, functional scope, or specific application of AI in controlling. Future research should therefore use larger samples, longitudinal data, and more detailed measures of AI adoption to examine whether and under what conditions AI-enabled controlling contributes to improved financial performance over time.

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