Does a Client's Digital Transformation Affect Audit Quality and Audit Inputs? Evidence from China

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ABSTRACT In the digital economy era, digital transformation has become a key strategy for enterprises to improve competitiveness. This study uses data from Shanghai and Shenzhen A-share listed companies in China from 2010 to 2023 to examine the impact of corporate digital transformation on audit quality and audit inputs. The results show that digital transformation significantly improves audit quality by enhancing internal control and information transparency. At the same time, it increases audit inputs because of greater operational and system complexity. The effects exhibit significant heterogeneity across audit firms. Non-Big Four auditors achieve greater audit-quality improvement but face substantially increased audit effort, while Big Four firms experience limited changes in both audit quality and audit inputs. The findings reveal a digital divide in audit capabilities, in which technological disparities between large and small audit firms lead to different adaptation patterns. This study provides empirical evidence for understanding how enterprise digital transformation reshapes audit risk assessment, audit-resource allocation, and audit-service quality in the digital economy.

INDEX TERMS digital transformation, audit quality, audit inputs, internal control, information transparency

I. INTRODUCTION

THE robust expansion of the digital economy, propelled by technologies such as artificial intelligence (AI), blockchain, cloud computing, big data, and the Internet of Things, has become a pivotal force in driving global economic growth and reshaping competitive landscapes. Digital technologies have revolutionized enterprise operations, redefined competitive advantages, and introduced a new intrinsic catalyst for high-quality development, restructuring, and upgrading of businesses. Consequently, digital transformation (DT) has emerged as a critical approach for revitalizing traditional growth drivers and fostering new developmental catalysts. The adoption of DT has become an imperative choice for enterprises seeking to bolster their competitiveness and achieve superior developmental outcomes [1]. As a cornerstone of traditional manufacturing, the industry's shift toward intelligent production and digital supply chains exemplifies this broader economic trend, providing a relevant context for examining how technological advancement affects corporate governance.

The impact of enterprise DT on firm value, internal operations, and market competitiveness is profound [2,3]. Firms adopting DT utilize technologies like big data, cloud computing, and AI to streamline information management, diversify communication channels, and enhance data transmission speed and accuracy, thereby reducing information asymmetry [4]. However, DT entails more than technological adoption; it represents a fundamental overhaul of business models, operational processes, and value creation methods. This comprehensive change involves changes in governance structures, control mechanisms, operational paradigms, and organizational culture [5]. While offering benefits, it also introduces strategic, operational, and financial risks [6]. The resulting complexity heightens challenges in recognition, measurement, and reporting of items within financial statements [7,8], raising concerns about auditors' ability to accurately identify risks, implement appropriate audit procedures, and maintain audit quality in digitally transformed enterprises. Moreover, the managerial capabilities of Chinese enterprises often lag behind the rapid advancement of digital technologies. Consequently, many firms struggle to seamlessly integrate digital innovations into their business processes, resulting in underwhelming performance improvements post-transformation [1]. This disparity underscores the potential for increased uncertainty and risk in the Chinese business landscape, thereby potentially impacting audit processes.

This study explores the impact of enterprise DT on audit quality and audit inputs, focusing on a sample of Shanghai and Shenzhen A-share listed companies from

2010 to 2023. Our findings reveal that DT significantly enhances audit quality, primarily through improved internal controls and greater information transparency. However, this improvement comes at a cost as auditors must increase their inputs to address the complexities introduced by digital technologies, leading to higher audit fees. These results suggest that for traditional sectors, DT is a “double-edged sword” for auditors, as it mitigates information asymmetry but demands more sophisticated procedures to address the complexity of digitalized production processes. Notably, these effects are more pronounced for clients of non-Big Four accounting firms, highlighting a new form of digital divide within the audit profession. While non-Big Four firms benefit from enhanced audit quality, they also face rising costs, potentially undermining their competitive position in the market. In contrast, Big Four firms, with their advanced technological infrastructure, experience marginal changes in audit quality and inputs, leveraging their reputation to command fee premiums.

This study contributes to the literature in several ways. First, it provides valuable insights into the interaction among technology, management systems, and audit practices, deepening our understanding of the practical effects of DT—particularly on audit quality and inputs within the digital economy. While prior studies have examined the impact of enterprise systems (ES) on audit quality and efficiency, this study distinguishes between ES and DT [9]. ES focus on optimizing core business processes through advanced software, whereas DT entails broader, fundamental changes to business activities, processes, and models to fully leverage digital technologies. The complexity of DT introduces greater challenges in identification, measurement, and reporting, leading to higher uncertainty and risks, which may uniquely affect audit processes. This research thus enriches the understanding of how DT shapes auditing.

Second, it offers robust empirical evidence on the dualistic impact of DT on auditing: while it can enhance audit quality through improved internal controls and information transparency, it simultaneously raises audit costs due to increased complexity and auditor effort. This finding extends prior research on technology in auditing by moving beyond simple narratives of efficiency gains to recognize the inherent trade-offs. Third, the findings reveal a growing digital divide within the audit profession. Non-Big Four firms, despite achieving higher audit quality, face disproportionately higher increases in audit inputs and fees compared to Big Four firms. This highlights the competitive challenges smaller audit firms encounter in adapting to DT, providing insights into the evolving audit market.

Finally, while managers widely believe that digital technologies can improve audit efficiency and reduce costs [10], this study provides first-time empirical evidence that DT may actually increase audit fees. This shift could exacerbate the growing tension and expectation gap regarding fees between managers and audit partners, thereby responding to and extending the related research [11].

II. LITERATURE REVIEW AND RESEARCH HYPOTHESES

A. LITERATURE REVIEW

Audit quality is a crucial metric in capital markets, influencing investor decisions and market health. DeAngelo defined it as contingent on auditors’ ability to detect and willingness to report accounting irregularities, reflecting both professional competence and independence [12]. Key influencing factors include auditor effort [13], client governance [14], corporate strategic transformation [15], and regulation [16].

In the digital economy, firms increasingly undergo DT to enhance competitiveness [1], optimizing processes, improving efficiency, fostering innovation, and increasing value [17,18]. However, this also introduces new risks and internal control challenges [5], requiring auditors to adapt methods and deepen understanding of clients’ digital systems [19,20].

Research presents mixed findings on DT and audit risk. Some studies indicate it increases audit risk and fees [21], including through blockchain adoption [22]. Others argue it reduces risk by strengthening internal controls and financial reporting quality [23-25]. Pincus et al. found ES improved certain audit quality metrics but did not aid in early material weakness detection. Importantly, ES—focused on optimizing core processes via software [26]—differs from holistic DT, which fundamentally reshapes business models and operations to leverage digital opportunities [27]. This broader transformation significantly impacts firm value, operations, and competitiveness [2,3], increasing business complexity and identification/measurement challenges [7,8]. For Chinese firms, which often struggle to integrate digital technologies effectively [1], transformation may introduce heightened uncertainty and risk, potentially affecting audit outcomes differently.

Regarding audit firms’ DT, the profession anticipates benefits like enhanced efficiency, data analysis, and audit quality [28,29]. However, a substantial body of research has identified the potential for digital technologies to exert a negative influence on individual behaviour [30], whereby individuals may exhibit algorithm aversion, underestimate AI-generated information, and overestimate information provided by human experts [31,32]. Furthermore, even when individuals receive feedback indicating that the algorithmic prediction is more accurate than their own, algorithm aversion persists [31].

Given these limited and mixed findings, this study examines the impact of enterprise DT on audit quality and audit inputs using a large sample of Chinese listed companies from 2010–2023.

B. RESEARCH HYPOTHESES

1) DT and Audit Quality

DT represents a fundamental restructuring of organizational operations and value creation through the integration of advanced digital technologies. This process has been shown to enhance corporate innovation and enterprise value

[17,18,33]. In the context of auditing, DT reduces information asymmetry and improves corporate transparency by enhancing information processing and communication through technologies like big data, AI, and cloud computing [4,8,34]. The resulting improvements in internal control quality and information transparency can reduce audit risk, thereby contributing to higher audit quality.

However, DT also entails significant organizational change, which can amplify inherent and control risks [5]. This increased risk profile may compel auditors to expand their procedures and resource allocation to maintain acceptable audit risk levels. Furthermore, DT fundamentally alters the nature, format, and volume of audit evidence [7], requiring auditors to develop new technical skills and methodologies. This increased audit input is itself positively associated with audit quality [13].

Drawing from this comprehensive analysis, we postulate the following hypothesis:

H1: The DT initiatives undertaken by an enterprise positively influence the audit quality of its annual financial report.

2) The Impact of DT on Internal Control Quality and Information Disclosure Transparency

DT fundamentally strengthens a firm's internal control framework. The adoption of technologies such as big data analytics, artificial intelligence, and blockchain enables automated, continuous, and real-time monitoring of business processes and transactions [35]. This technological integration allows for more precise risk identification and prompt corrective actions, thereby increasing the effectiveness of control activities. Furthermore, the inherent features of these technologies (e.g., the immutability of blockchain) enhance data integrity and reliability, which are foundational to a robust control environment [35]. The deployment of intelligent systems also facilitates the automated detection of control deviations or deficiencies, leading to more timely remediation [8]. Collectively, these advancements elevate the overall design and operational effectiveness of internal controls. High-quality internal controls provide auditors with greater assurance regarding the reliability of financial reporting processes, allowing for more efficient risk assessment and potentially reducing the extent of substantive testing, which contributes to higher audit quality [2]. The observed improvement in internal control quality reflects the net effect of digital transformation in strengthening control design, automation, and continuous monitoring, even though DT may simultaneously increase system complexity. In this study, the internal control index captures the effectiveness of control activities and the absence of material weaknesses, and thus provides a reasonable proxy for this overall enhancement in control quality. At the same time, stronger internal controls do not necessarily make the audit process less complex. Evaluating the design and operating effectiveness of technology-enabled controls often requires specialized IT audit expertise and additional audit effort. Therefore, improvements in internal control quality and increases in audit complexity may coexist.

Concurrently, DT significantly improves the quality and transparency of corporate information. Advanced data processing and analytics capabilities allow firms to integrate and analyze information from diverse sources and formats more efficiently [8]. This optimization of the information management process minimizes delays and errors in internal and external reporting, leading to more timely, accurate, and comprehensive disclosures [8, 27]. Improved information transparency reduces information asymmetry between management and external stakeholders. Crucially, it restricts opportunities for managerial opportunism, such as earnings manipulation, by increasing the visibility and traceability of business activities [36]. For auditors, access to higher-quality and more transparent information facilitates a more accurate identification and assessment of audit risks. It also streamlines evidence gathering and verification procedures, thereby improving the effectiveness of the audit process [37].

In summary, DT elevates audit quality not only directly but also indirectly by creating a more reliable information environment and a stronger internal control foundation within the auditee. These improvements provide auditors with a higher-quality basis for their professional judgments and procedures.

H2: The DT initiatives of enterprises enhance audit quality by improving internal control systems.

H3: The DT efforts of enterprises elevate audit quality through improvements in information disclosure transparency.

3) DT's Impact on Audit Inputs

The theoretical impact of enterprise DT on audit inputs is not unidirectional. The extant literature presents two distinct and potentially countervailing theoretical perspectives, from which competing hypotheses can be logically derived.

From one perspective, DT is posited to enhance audit efficiency and reduce necessary effort. DT significantly improves corporate information management processes by minimizing delays and errors in information flow, thereby enhancing the quality and relevance of accounting data [8]. This results in greater corporate information transparency and higher accounting information quality [27,37]. For auditors, access to more transparent and high-quality information lowers the barriers to data acquisition and verification, potentially saving time and resources. Smoother communication with management, facilitated by a shared understanding of clearer information, can reduce the time required for clarifications and reconciliations.

Concurrently, DT strengthens internal control quality through automation, improved data accuracy, and realtime operational insights [35]. More reliable internal controls reduce the likelihood of errors and fraud, ensuring financial data is more dependable. This increased reliability allows auditors to place greater reliance on the client's internal systems and may reduce the extent of substantive testing required, leading to lower overall audit effort and cost.

Therefore, from this efficiency-focused perspective, we derive the following hypothesis:

H4a: Enterprise DT reduces auditors' inputs.

An opposing perspective emphasizes the challenges and complexities introduced by DT. DT fundamentally reshapes business models, operational processes, and governance structures [5]. This comprehensive organizational change can escalate inherent and control risks, compelling auditors to expand procedures and resource allocation to mitigate these emerging risks. The digital metamorphosis generates vast and intricate datasets, requiring auditors to dedicate increased time to data analysis and validation [38,39]. While technologies like blockchain enhance data integrity, they also necessitate complex verification procedures, such as reconciling on-chain and off-chain data, thereby augmenting audit complexity and duration.

Furthermore, in the Chinese context, managerial capabilities often lag behind technological advancements, leading many firms to struggle with effective digital integration and underwhelming post-transformation performance [1]. This gap introduces heightened business uncertainty and risk that auditors must address through expanded testing. From the auditor's side, adapting to new digital environments requires significant investment in learning and skill development [39,40]. Auditors, particularly those in domestic Chinese firms which generally exhibit lower levels of informatization compared to the international Big Four, may lack specialized IT expertise [41]. This can compel them to conduct more extensive substantive procedures and expand control testing samples to compensate, thereby increasing audit inputs.

Consequently, based on this complexity and risk perspective, we propose the competing hypothesis:

H4b: Enterprise DT increases auditors' inputs.

Given these theoretically grounded but opposing predictions, this study empirically tests which of the two countervailing effects, the efficiency gain or the complexity-driven increase, dominates in the context of Chinese listed companies.

III. RESEARCH DESIGN

A. SAMPLE SELECTION AND DATA SOURCES

This study focuses on Shanghai and Shenzhen A-share listed companies spanning the period from 2010 to 2023. The sample selection process involved the following criteria:
(1) exclusion of listed financial institutions;
(2) omission of companies with irregular listing statuses; and
(3) elimination of entities with incomplete data.

Post-screening, the final sample comprises 37,173 firm-year observations. All relevant data were extracted from the China Stock Market & Accounting Research (CSMAR) database. To mitigate the influence of outliers, continuous variables in the sample dataset underwent winsorization at the 1st and 99th percentiles.

B. VARIABLES AND MODEL SPECIFICATION

1) Dependent Variable: Audit Quality

This research employs the modified Jones model proposed by Dechow et al. [42], utilizing the methodology outlined by Defond and Jiambalvo [43]. Initially, non-discretionary accruals are estimated for each firm, and discretionary accruals are then derived. The absolute value of discretionary accruals (AbsDA) is used as a proxy for audit quality. A higher AbsDA value indicates a greater degree of corporate earnings management and, consequently, lower audit quality. The specific calculation formula is delineated below.

$$\begin{aligned}
\frac{TA_{i,t}}{A_{i,t-1}} &= \alpha\frac{1}{A_{i,t-1}} + \beta\frac{\Delta REV_{i,t} - \Delta REC_{i,t}}{A_{i,t-1}} + \gamma\frac{PPE_{i,t}}{A_{i,t-1}} + \epsilon \\
\frac{NDA_{i,t}}{A_{i,t-1}} &= \hat{\alpha}\frac{1}{A_{i,t-1}} + \hat{\beta}\frac{\Delta REV_{i,t} - \Delta REC_{i,t}}{A_{i,t-1}} + \hat{\gamma}\frac{PPE_{i,t}}{A_{i,t-1}} \\
\frac{DA_{i,t}}{A_{i,t-1}} &= \frac{TA_{i,t}}{A_{i,t-1}} - \frac{NDA_{i,t}}{A_{i,t-1}} \\
AbsDA_{i,t} &= \left|\frac{DA_{i,t}}{A_{i,t-1}}\right|.
\end{aligned} \tag{1}$$

In Equation (1), $NDA_{i,t}$ denotes non-discretionary accruals for firm i in year t, and $TA_{i,t}$ represents total accruals for the same firm-year. $A_{i,t-1}$ is total assets at the end of year $t-1$. $\Delta REV_{i,t}$ is the change in operating revenue for firm i in year t, and $\Delta REC_{i,t}$ is the change in accounts receivable. $PPE_{i,t}$ denotes net property, plant, and equipment. ϵ is the residual term, and T represents the number of years in the estimation.

Following Knechel and Payne [44], we measure audit report lag as the natural logarithm of the number of days between the fiscal year-end and the audit report date, termed AuditLag, to proxy for auditors' time investment.

2) Independent Variable: Enterprise DT Intensity

This study adopts the methodology proposed by Wu et al. and Kindermann et al. to construct proxy variables for enterprise DT through textual analysis [4,45]. The process involves initially compiling and filtering keywords associated with DT. Subsequently, the Jieba module in Python is employed to quantify the frequency of these keywords within the annual reports of listed companies. During the frequency analysis, keywords preceded by negative terms such as "none" or "no" are disregarded. Furthermore, keywords not directly describing the company are eliminated from consideration. Finally, based on the data pool formed by extracting the annual reports of listed companies using Python, feature words from Table 1 are searched, matched, and their word frequencies are counted. Subsequently, the key technology directions are classified and aggregated according to word frequency, and the total word frequency is calculated to construct an indicator system for enterprise DT [4]. Given the right-skewed distribution of keywords frequencies, the word counts are log-transformed after adding one to construct the DT indicator (DCG_word). To facilitate empirical analysis and maintain consistency with other variables' magnitudes, this indicator is scaled down by a factor of 100. It's important to note that this scaling does not alter the relationships between variables or impact the model's predictive capabilities.

3) Mediating Variables

This research utilizes the internal control index (IC) as a measure of internal control quality, sourced from the DIB database. The assessment of information disclosure transparency for listed companies utilizes the Disclosure evaluation outcome. Annually, both the Shanghai and Shenzhen Stock Exchanges conduct evaluations, categorizing results into four tiers: A (excellent), B (good), C (qualified), and D (unqualified). This study assigns numerical values of 1, 2, 3, and 4 to these grades, respectively, in descending order of quality. Consequently, a higher assigned value correlates with diminished information transparency for any given listed company.

4) Model and Control Variables

To examine the influence of enterprise DT on audit quality, the following regression model is constructed to test H1:

$$AbsDA_{i,t} = \beta_0 + \beta_1 DCG\_word_{i,t} + \sum_m \beta_m Control_{m,i,t} + \epsilon_{i,t} \tag{2}$$

To investigate potential mediating effects and mitigate estimation bias stemming from collinearity, this study adopts a two-step approach, referencing Jiang, to validate H2 [46]. Initially, Equation (2) is used to verify the total effect. Subsequently, Equation (3) is employed to assess the impact of enterprise DT on the mediators. In Equation (3), the term Mediator encompasses IC and Disclosure.

$$Mediator_{i,t} = \beta_0 + \beta_1 DCG\_word_{i,t} + \sum_m \beta_m Control_{m,i,t} + \epsilon_{i,t} \tag{3}$$

This study selects the following variables that may significantly impact audit quality, based on similar research: company size (Size), debt-to-equity ratio (LEV), book-to-market ratio (BM), Tobin's Q (TobinQ), cash flow ratio (Cashflow), accounts receivable ratio (REC), fixed asset ratio (FIXED), executive remuneration (TMTPay), management ownership percentage (MShare), ownership concentration (Balance), years listed on the stock exchange (ListAge), large shareholder's occupation (Occupy), auditor's opinion (Opinion), audit fees (AuditFee). Table 2 shows the definitions of the variables.

IV. ANALYSIS OF EMPIRICAL FINDINGS

A. STATISTICAL OVERVIEW

Table 3 presents a summary of the key variables examined in this study. The average value of the dependent variable (AbsDA) is calculated at 0.0664, with a median of 0.0445. For the independent variable (DCG_word), the mean stands at 0.0150, suggesting that Chinese enterprises still have considerable potential for advancing their DT efforts. Furthermore, the standard deviation is 0.0143, ranging from a minimum of 0 to a maximum of 0.0519. This spread indicates a significant disparity in the extent of DT among different companies. When these figures are scaled up by a factor of 100, they align closely with the outcomes reported by Wu et al. (2021).

V. EXAMINATION OF REGRESSION RESULTS

A. THE EFFECT OF CLIENT'S DT ON AUDIT QUALITY

To evaluate H1, we conducted a regression analysis exploring the relationship between corporate DT and audit quality, utilizing Equation (2). The outcomes are displayed in Table 4. The initial column controls for year and industry fixed effects without including any control variables. The findings reveal a statistically significant negative correlation between corporate DT and audit quality at the 1% level. The regression coefficient for DCG_word is -0.138, suggesting that as the degree of corporate DT increases, there is a corresponding improvement in audit quality. This preliminary result lends support to H1. In the second column, which incorporates both year and industry fixed effects along with control variables, the regression coefficient for DCG_word is -0.13 (t = -3.84), achieving significance at the 1% level. This outcome further corroborates that a higher degree of corporate DT is associated with enhanced audit quality, thereby reinforcing H1.

B. EXAMINING THE INTERMEDIARY ROLE OF INTERNAL CONTROL EFFICACY AND INFORMATION DISCLOSURE TRANSPARENCY

To test whether DT enhances audit quality by improving internal control systems and information disclosure transparency (H2 and H3), we first establish the baseline relationship. Column (2) of Table 4 confirms a significant negative relationship between DT (DCG_word) and discretionary accruals (AbsDA, coefficient = – 0.130, t = –3.84), which serves as the foundation for the mediation analysis.

We then examine the effect of DT on the proposed mediators. As shown in Table 5, DCG_word has a significantly positive coefficient (0.353, t = 3.62) when the internal control index (IC) is the dependent variable, indicating that DT strengthens internal controls. In column (2) of Table 5, DCG_word exhibits a significantly negative coefficient (–0.634, t = –2.16) when information disclosure transparency (Disclosure) is the dependent variable (where a lower score indicates higher transparency), suggesting that DT enhances information transparency. These results satisfy the precondition for mediation: DT significantly influences both mediators.

To formally test the significance of the indirect pathways, we employ a stepwise regression approach and conduct the Sobel–Goodman mediation test. Table 6 reports the stepwise regression results and the mediation test statistics. The Sobel test Z-value for the internal control pathway is –1.957 (p =

TABLE 1. Structured Feature Word Map of Enterprise DT

Technology Category	Details
Artificial Intelligence	Artificial intelligence, business intelligence, image understanding, investment decision support systems, intelligent data analysis, intelligent robots, machine learning, deep learning, semantic search, biometric technology, face recognition, speech recognition, identity verification, autonomous driving, natural language processing
Big Data Technology	Big data, data mining, text mining, data visualization, heterogeneous data, credit investigation, augmented reality, mixed reality, virtual reality
Cloud Computing	Cloud computing, stream computing, graph computing, in-memory computing, secure multi-party computation, brain-inspired computing, green computing, cognitive computing, integrated architecture, billion-level concurrency, exabyte-level storage, Internet of Things, cyber-physical systems
Blockchain Technology	Blockchain, digital currency, distributed computing, differential privacy technology, smart financial contracts
Digital Technology Applications	Mobile internet, industrial internet, mobile interconnection, internet healthcare, e-commerce, mobile payment, third-party payment, NFC payment, smart energy, B2B, B2C, C2B, C2C, O2O, online connectivity, smart wearables, smart agriculture, smart transportation, smart healthcare, smart customer service, smart homes, smart investment advisory, smart tourism, smart environmental protection, smart grids, smart marketing, digital marketing, unmanned retail, internet finance, digital finance, fintech, quantitative finance, open banking

TABLE 2. The definitions of the variables

Variable Category	Variable Name	Definition
Interpreted variable	AbsDA	The absolute value of discretionary accruals, estimated using the modified Jones model
Explanatory variable	DCG_word	The natural logarithm of (1 + the frequency of digitization-related words in the annual report) divided by 100
Control variables	Size	The natural logarithm of total assets at the end of the period
	Lev	The ratio of total liabilities to total assets at the end of the period
	BM	The ratio of a firm's book value to its market capitalization
	TobinQ	(Market value of tradable shares + number of non-tradable shares × net asset value per share + book value of liabilities) / total assets
	Cashflow	The ratio of net operating cash flow to total assets
	REC	The ratio of net accounts receivable to total assets
	INV	The ratio of net inventory to total assets
	FIXED	The ratio of net fixed assets to total assets
	TMTPay	The natural logarithm of the total compensation of the top three executives in a listed company
	Mshare	The proportion of shares held by management divided by total share capital
	Balance	The ratio of the combined shareholding percentages of the second to fifth largest shareholders to the shareholding percentage of the largest shareholder
	AuditFee	The natural logarithm of audit fees
	ListAge	The natural logarithm of (current year - year of listing + 1)
	Occupy	The ratio of other receivables to total assets
	Opinion	A dummy variable equal to 1 for a standard unqualified opinion and 0 for other audit opinions
Fixed effects	Industry	Industry dummy variables
	Year	Year dummy variable

TABLE 3. Statistical Summary of Key Variables

(1) VARIABLES	(2) N	(3) mean	(4) sd	(5) min	(6) median	max
AbsDA	37,173	0.0664	0.0711	0.0008	0.0445	0.400
DCG_word	37,173	0.0150	0.0143	0	0.0139	0.0519
Size	37,173	22.25	1.260	19.98	22.06	26.14
Lev	37,173	0.426	0.205	0.0557	0.419	0.899
BM	37,173	0.621	0.250	0.119	0.617	1.198
TobinQ	37,173	2.037	1.292	0.835	1.620	8.434
Cashflow	37,173	0.0466	0.0682	-0.156	0.045	0.241
REC	37,173	0.123	0.102	0.000281	0.101	0.462
INV	37,173	0.142	0.130	0.000273	0.111	0.699
FIXED	37,173	0.208	0.155	0.00226	0.176	0.683
TMTPay	37,173	14.63	0.707	12.97	14.60	16.60
Mshare	37,173	13.33	19.11	0	0.850	67.51
Balance	37,173	0.749	0.609	0.0298	0.585	2.790
AuditFee	37,173	13.73	0.627	12.61	13.63	15.80
ListAge	37,173	2.192	0.783	0.693	2.303	3.401
Occupy	37,173	0.0144	0.0221	0.000133	0.007	0.135
Opinion	37,173	0.969	0.174	0	1	1

0.050), and for the information transparency pathway it is –2.013 ($p = 0.044$), both indicating statistically significant mediation effects. In addition, when both DCG_word and the mediator (IC) are included in the regression for AbsDA, the coefficient on IC remains significant while the coefficient on DCG_word is reduced in magnitude, supporting partial mediation. H2 and H3 are verified.

TABLE 4. Impact of DT on Audit Quality

	(1) AbsDA	(2) AbsDA
DCG_word	-0.138***	-0.130***
	(-5.33)	(-3.84)
Size		-0.004***
		(-7.47)
Lev		0.035***
		(15.07)
BM		-0.023***
		(-7.90)
TobinQ		0.002***
		(4.37)
Cashflow		-0.132***
		(-23.51)
REC		0.007
		(1.61)
INV		0.019***
		(5.02)
FIXED		0.002
		(0.60)
TMTPay		0.002***
		(3.29)
Mshare		0.000***
		(3.21)
Balance		0.002***
		(2.82)
AuditFee		0.003***
		(3.87)
ListAge		-0.002***
		(-2.79)
Occupy		0.066***
		(3.87)
Opinion		-0.028***
		(-13.77)
Constant	0.069***	0.110***
	(128.00)	(10.09)
Industry	No	Yes
Year	No	Yes
N	37173	37172
R2	0.001	0.138
Adj. R2	0.001	0.137

Note: The values in parentheses represent t-values. Significance levels are denoted as follows: *** for 1%, ** for 5%, and * for 10%. This notation is used throughout the paper.

C. CLIENT'S DT AND AUDIT INPUTS

The regression results in Table 7 demonstrate that DT (DCG_word) significantly increases audit lag (β = 0.608, $p < 0.01$), even after controlling for firm characteristics and fixed effects. This finding supports hypothesis H4b, suggesting that enterprise DT increases auditors' inputs in the Chinese context. While DT improves information quality and internal controls (as noted in H4a), the findings suggest that in China's context, the dominant effect stems from the increased complexity and transitional challenges of digital adoption. Auditors face heightened demands to verify intricate digital systems (e.g., blockchain data reconciliation), address elevated inherent risks from unproven digital business models, and compensate for firms' managerial gaps in technology integration—all requiring expanded testing procedures and adaptation time.

D. THE DIFFERENTIAL IMPACT OF DT ON AUDIT QUALITY AND AUDIT INPUT BETWEEN BIG FOUR AND NON-BIG FOUR FIRMS

The Big Four international accounting firms, with their superior technological resources and global operational networks, hold a leading position in information technology implementation [39,41]. Conversely, Chinese domestic accounting firms lag in this aspect, potentially leading to significant variations in audit quality when serving highly digitally transformed clients. This study employs the Big Four versus non-Big Four dichotomy as a well-established proxy for systematic differences in audit firms' technological capabilities [39,41]. To examine whether these differential capabilities moderate the impact of client DT, we conduct separate subgroup analyses.

Results in Table 8 reveal a distinct divergence in outcomes. For audit quality (AbsDA), client DT (DCG_word) shows no significant effect for Big Four clients (coefficient = 0.248, t = 1.60) but leads to significant quality improvement for non-Big Four clients (coefficient = -0.155, t = -4.46).

TABLE 5. Intermediary effect of IC quality and information disclosure transparency

	(1) IC	(2) Disclosure
DCG_word	0.353***	-0.634**
	(3.62)	(-2.16)
Size	0.026***	-0.238***
	(16.45)	(-48.02)
Lev	-0.064***	0.564***
	(-9.52)	(27.03)
BM	-0.002	0.335***
	(-0.19)	(12.93)
TobinQ	0.001	-0.005
	(0.71)	(-1.25)
Cashflow	0.035**	-0.783***
	(2.17)	(-15.50)
REC	0.046***	-0.250***
	(3.77)	(-6.83)
INV	-0.005	-0.255***
	(-0.44)	(-7.46)
FIXED	-0.009	0.004
	(-1.00)	(0.15)
TMTPay	0.023***	-0.068***
	(12.50)	(-11.57)
Mshare	0.000	-0.001***
	(0.62)	(-3.24)
Balance	0.001	0.054***
	(0.48)	(10.50)
AuditFee	-0.020***	0.103***
	(-8.18)	(13.34)
ListAge	-0.018***	0.082***
	(-10.69)	(15.63)
Occupy	-0.321***	2.513***
	(-6.52)	(16.02)
Opinion	0.156***	-0.984***
	(26.29)	(-54.41)
Constant	2.842***	7.235***
	(90.81)	(73.47)
Industry	Yes	Yes
Year	Yes	Yes
N	37131	31783
R2	0.289	0.269
Adj. R2	0.288	0.267

Notes: t-values are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Regarding audit inputs (AuditLag), DT increases effort for both groups, but the effect is more statistically significant for non-Big Four firms (0.557, t = 5.89) than for Big Four firms (0.655, t = 1.80).

This disparity in outcomes can be explained by the differential resource endowments and adaptation capacities of the two auditor types. For non-Big Four auditors, client digitalization acts as a capability-enhancing complement. The improved information transparency and structured data flow from digitally transformed clients [8] help mitigate these auditors' inherent technological gaps. This facilitates more effective audit procedures and reduces information asymmetry [2], leading to the observed significant improvement in audit quality (AbsDA). However, achieving this quality gain requires substantial adaptive investment, as non-Big Four firms must devote considerable effort to understanding new digital systems and expanding their testing scope, resulting in a pronounced increase in audit lag.

In contrast, Big Four firms possess established advantages through their advanced proprietary technologies, standardized global audit methodologies, and refined operational frameworks. This integrated infrastructure enables them to incorporate the procedural adjustments demanded by client DT with notable efficiency. Consequently, they exhibit only marginal increases in audit lag and statistically insignificant net changes in audit quality metrics—a pattern consistent with diminishing returns on an already elevated baseline. This result should not be interpreted as evidence of limited procedural adjustment. Rather, it reflects the greater adaptability, more advanced technological infrastructure, and higher process efficiency of Big Four firms, which enable them to absorb the impact of client DT with less incremental audit input and with limited observable changes in quality metrics. Untabulated results indicate that the audit quality is significantly higher for clients of Big Four accounting firms than that for those of non-Big Four firms (0.057 vs. 0.067 t = 6.60). The modest increase in audit inputs for Big Four firms thus reflects their institutional capacity to assimilate added complexity within existing efficient systems. This stands in clear contrast to the substantial adaptive investment

TABLE 6. Sobel-Goodman Test for the mediating effect of IC Quality and Information Disclosure Transparency

	(1) AbsDA	(2) IC	(3) AbsDA
DCG_word	-0.128***	0.353***	-0.127***
	(-3.80)	(3.62)	(-3.75)
IC			-0.004**
			(-2.33)
Size	-0.004***	0.026***	-0.004***
	(-7.41)	(16.45)	(-7.18)
Lev	0.035***	-0.064***	0.035***
	(15.00)	(-9.52)	(14.87)
BM	-0.023***	-0.002	-0.023***
	(-7.86)	(-0.19)	(-7.87)
TobinQ	0.002***	0.001	0.002***
	(4.40)	(0.71)	(4.41)
Cashflow	-0.132***	0.035**	-0.132***
	(-23.44)	(2.17)	(-23.41)
REC	0.007	0.046***	0.007*
	(1.61)	(3.77)	(1.65)
INV	0.019***	-0.005	0.019***
	(5.07)	(-0.44)	(5.07)
FIXED	0.002	-0.009	0.002
	(0.71)	(-1.00)	(0.69)
TMTPay	0.002***	0.023***	0.002***
	(3.27)	(12.50)	(3.42)
Mshare	0.000***	0.000	0.000***
	(3.20)	(0.62)	(3.21)
Balance	0.002***	0.001	0.002***
	(2.85)	(0.48)	(2.86)
AuditFee	0.003***	-0.020***	0.003***
	(3.83)	(-8.18)	(3.73)
ListAge	-0.002***	-0.018***	-0.002***
	(-2.87)	(-10.69)	(-2.99)
Occupy	0.069***	-0.321***	0.068***
	(4.05)	(-6.52)	(3.97)
Opinion	-0.028***	0.156***	-0.027***
	(-13.49)	(26.29)	(-13.06)
_cons	0.109***	2.842***	0.121***
	(10.04)	(90.81)	(10.07)
Industry	Yes	Yes	Yes
Year	Yes	Yes	Yes
N	37131	37131	37131
R2	0.138	0.289	0.138
Adj. R2	0.137	0.288	0.137
Statistic	Z	$p > \|Z\|$	
Sobel	-1.957	0.050	
Goodman-1	-1.906	0.057	
Goodman-2	-2.013	0.044	
Proportion of mediating effect	0.012/1.012 = 0.012		

Notes: t-values are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

It should be noted that the improvement in the internal control quality index reflects the strengthening of control design and monitoring capabilities through DT, such as the implementation of automated controls and real-time oversight. This suggests auditors may place greater reliance on these enhanced controls. However, this increased reliance does not equate to a reduction in audit complexity; rather, validating these sophisticated, technology-driven controls often demands greater auditor effort and specialized expertise, as discussed in relation to audit inputs (H4b).

required of non-Big Four auditors. In essence, while client digitalization demands significant resource allocation from non-Big Four firms, it primarily necessitates manageable operational refinements within Big Four firms' established technological and methodological frameworks.

VI. ROBUSTNESS TEST

A. SUBSTITUTION OF VARIABLES

In order to further accurately portray the indicators of the degree of enterprise DT, this paper constructs enterprise DT indicators from two aspects: the breadth of the use of digital technology and the depth of the application of digital technology [47]. Breadth of digital technology use is assessed through four key digital technologies: big data, artificial intelligence, cloud computing, and blockchain. Relevant keywords are extracted from the annual reports of enterprises to evaluate their adoption of these technologies. The depth of digital technology application is evaluated by focusing on two aspects: digital management and digital

TABLE 7. DT and Audit Inputs

	(1) AuditLag	(2) AuditLag
DCG_word	2.283***	0.608***
	(32.43)	(6.61)
Size		-0.015***
		(-9.88)
Lev		0.046***
		(7.18)
BM		0.036***
		(4.49)
TobinQ		-0.005***
		(-3.47)
Cashflow		-0.169***
		(-11.03)
REC		-0.024**
		(-2.06)
INV		-0.018*
		(-1.76)
FIXED		-0.056***
		(-6.75)
TMTPay		-0.016***
		(-8.99)
Mshare		0.000
		(0.53)
Balance		0.002
		(1.36)
AuditFee		0.033***
		(14.27)
ListAge		-0.014***
		(-8.61)
Occupy		0.271***
		(5.83)
Opinion		-0.090***
		(-16.13)
_cons	4.550***	4.791***
	(3113.32)	(162.22)
N	37128	37127
Industry	Yes	Yes
Year	Yes	Yes
R2	0.028	0.167
Adj. R2	0.028	0.166

Notes: t-values are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

production. Keywords are screened based on these dimensions to gauge how deeply these technologies are embedded in the company's operations.

As shown in Table 9, the breadth and depth of the application of digital technology have significantly improved the quality of audits (-0.001, t=-2.78; -0.001, t=-2.98 respectively) and increased audit inputs (0.003, t=2.79; 0.007, t=6.28 respectively). This further supports our hypothesis 1 and 4b, proving that the results are robust.

B. INSTRUMENTAL VARIABLES

To address potential endogeneity concerns, particularly the possibility of reverse causality where firms with higher audit quality might be more likely to undergo DT, we employ instrumental variable (IV) analysis. This approach helps to isolate the causal effect of DT on audit outcomes. Following established literature, we use the annual industry average level of DT as instrumental variables. IV1 is the mean value of the degree of DT of other firms in the same industry in the same year (excluding current observation), and IV2 is the mean value of the degree of DT of the same industry in the same year (including current observation). The regression results are shown in Table 10.

The first-stage regression results in column (1) of Table 10 show that the selected instrumental variables are significantly positively correlated with the endogenous variable DCG_word at the 1% level, satisfying the relevance condition. The Wald F-statistics (167.91 and 435.50) far exceed the conventional threshold of 10, rejecting the hypothesis of weak instruments. The second-stage results in columns (2) and (3) show that the coefficients of DCG_word on AbsDA remain significantly negative, consistent with our baseline findings. The significant endogeneity test p-values (0.006 and 0.004) confirm the presence of endogeneity, justifying the use of IV estimation. These results strengthen the causal interpretation that DT leads to improved audit quality, rather than the reverse.

C. OTHER ENDOGENEITY TESTS

In addition to IV estimation, we implement several other strategies to further address endogeneity and selection bias. We utilized industry cluster-robust standard errors, imple-

TABLE 8. Audit Quality and Audit Inputs for the Big Four and Non-Big Four Firms

	Big Four AbsDA	Non-Big Four AbsDA	Big Four AuditLag	Non-Big Four AuditLag
DCG_word	0.248	-0.155***	0.655*	0.557***
	(1.60)	(-4.46)	(1.80)	(5.89)
Size	-0.008***	-0.004***	-0.018***	-0.013***
	(-3.56)	(-6.80)	(-3.56)	(-8.45)
Lev	0.031***	0.035***	0.007	0.037***
	(2.76)	(14.64)	(0.28)	(5.66)
BM	-0.011	-0.024***	0.081***	0.035***
	(-0.93)	(-7.82)	(2.98)	(4.23)
TobinQ	0.001	0.002***	0.010**	-0.004***
	(0.26)	(4.46)	(2.11)	(-3.10)
Cashflow	-0.022	-0.137***	-0.235***	-0.168***
	(-0.84)	(-23.82)	(-3.92)	(-10.70)
REC	-0.033*	0.008*	-0.220***	-0.020*
	(-1.69)	(1.80)	(-4.80)	(-1.67)
INV	0.040**	0.017***	-0.081**	-0.020*
	(2.39)	(4.56)	(-2.06)	(-1.93)
FIXED	0.036***	-0.001	-0.005	-0.060***
	(2.99)	(-0.41)	(-0.17)	(-7.06)
TMTPay	0.003	0.002***	-0.015**	-0.015***
	(1.20)	(3.12)	(-2.52)	(-7.87)
Mshare	0.000***	0.000**	0.000	-0.000
	(2.83)	(2.57)	(1.16)	(-0.05)
Balance	0.000	0.002***	0.002	0.002
	(0.15)	(2.76)	(0.33)	(1.27)
AuditFee	0.004	0.004***	0.022***	0.047***
	(1.24)	(4.65)	(2.74)	(18.56)
ListAge	-0.000	-0.002***	-0.032***	-0.014***
	(-0.15)	(-3.34)	(-5.37)	(-8.41)
Occupy	0.049	0.063***	-0.028	0.257***
	(0.66)	(3.58)	(-0.16)	(5.36)
Opinion	-0.024**	-0.028***	-0.150***	-0.087***
	(-2.04)	(-13.55)	(-5.34)	(-15.29)
Constant	0.131***	0.095***	5.027***	4.558***
	(2.86)	(7.83)	(46.99)	(138.86)
Industry	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
N	1932	35195	1932	35195
R2	0.147	0.140	0.260	0.172
Adj. R2	0.115	0.138	0.231	0.171

Notes: t-values are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

TABLE 9. Breadth and depth of digitalization and audit quality

	(1) AbsDA	(2) AbsDA	(1) AuditLag	(2) AuditLag
LogDeep	-0.001***		0.003***	
	(-2.78)		(2.79)	
LogWide		-0.001***		0.007***
		(-2.98)		(6.28)
Size	-0.004***	-0.004***	-0.014***	-0.015***
	(-7.46)	(-7.38)	(-9.44)	(-9.71)
Lev	0.035***	0.035***	0.045***	0.046***
	(15.02)	(14.94)	(7.05)	(7.18)
BM	-0.023***	-0.023***	0.035***	0.036***
	(-7.86)	(-7.88)	(4.33)	(4.52)
TobinQ	0.002***	0.002***	-0.005***	-0.004***
	(4.38)	(4.43)	(-3.47)	(-3.42)
Cashflow	-0.134***	-0.134***	-0.171***	-0.168***
	(-23.76)	(-23.85)	(-11.15)	(-10.98)
REC	0.006	0.007	-0.020*	-0.024**
	(1.50)	(1.60)	(-1.76)	(-2.07)
INV	0.020***	0.019***	-0.021**	-0.018*
	(5.30)	(5.15)	(-2.11)	(-1.81)
FIXED	0.003	0.003	-0.061***	-0.057***
	(0.97)	(0.87)	(-7.38)	(-6.93)
TMTPay1	0.002***	0.002***	-0.016***	-0.016***
	(3.36)	(3.34)	(-8.88)	(-8.96)
Mshare	0.000***	0.000***	0.000	0.000
	(3.29)	(3.22)	(0.58)	(0.63)
Balance2	0.002***	0.002***	0.002	0.002
	(2.66)	(2.68)	(1.36)	(1.30)
AuditFee	0.003***	0.003***	0.034***	0.034***
	(3.62)	(3.61)	(14.64)	(14.49)
ListAge	-0.002***	-0.002***	-0.014***	-0.014***
	(-2.81)	(-2.82)	(-8.57)	(-8.50)
Occupy	0.064***	0.064***	0.276***	0.275***
	(3.76)	(3.77)	(5.91)	(5.89)
Opinion	-0.028***	-0.028***	-0.090***	-0.091***
	(-13.63)	(-13.62)	(-16.06)	(-16.14)
_cons	0.111***	0.110***	4.770***	4.782***
	(10.23)	(10.14)	(161.60)	(161.80)
Industry	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
N	37041	37041	36996	36996
R2	0.139	0.139	0.166	0.167
Adj. R2	0.137	0.137	0.164	0.165

Notes: t-values are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

mented propensity score matching (PSM), and accounted for regional fixed effects. The PSM approach helps balance observable characteristics between firms with high and low levels of DT, thereby mitigating selection bias.

TABLE 10. Instrumental Variables Results

VARIABLE	(1) DCG_word	(2) IV1 AbsDA	(3) IV2 AbsDA
DCG_word		-1.500***	-1.019***
		(-2.91)	(-3.21)
IV1	0.005***		
	(12.96)		
IV2	0.009***		
	(20.87)		
N	37137	37137	37137
Endogeneity P-value		0.006	0.004
Wald F		167.91	435.50

Notes: t-values are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

TABLE 11. Robustness Test Results

	Cluster Robust Standard Error Correction AbsDA	PSM AbsDA	Regional Fixed Effects AbsDA
DCG_word	-0.130***	-0.004***	-0.130***
	(-3.23)	(-4.32)	(-3.84)
Size	-0.004***	-0.004***	-0.004***
	(-5.59)	(-7.37)	(-7.14)
Lev	0.035***	0.035***	0.035***
	(11.13)	(15.08)	(14.86)
BM	-0.023***	-0.023***	-0.024***
	(-6.65)	(-7.90)	(-8.05)
TobinQ	0.002***	0.002***	0.002***
	(3.29)	(4.43)	(4.29)
Cashflow	-0.132***	-0.132***	-0.133***
	(-13.67)	(-23.45)	(-23.51)
REC	0.007	0.007	0.007*
	(1.26)	(1.59)	(1.71)
INV	0.019***	0.019***	0.018***
	(3.42)	(5.05)	(4.95)
FIXED	0.002	0.002	0.001
	(0.49)	(0.77)	(0.42)
TMTPay	0.002***	0.002***	0.002***
	(2.79)	(3.33)	(2.99)
Mshare	0.000***	0.000***	0.000***
	(2.93)	(3.23)	(3.18)
Balance	0.002**	0.002***	0.002***
	(2.32)	(2.78)	(2.72)
AuditFee	0.003***	0.003***	0.003***
	(3.07)	(3.71)	(3.80)
ListAge	-0.002**	-0.002***	-0.002***
	(-2.45)	(-2.78)	(-2.72)
Occupy	0.066***	0.065***	0.064***
	(2.82)	(3.81)	(3.71)
Opinion	-0.028***	-0.028***	-0.028***
	(-9.64)	(-13.78)	(-13.69)
Constant	0.110***	0.110***	0.110***
	(8.23)	(10.09)	(9.86)
Industry	Yes	Yes	Yes
Firm	No	No	No
Year	Yes	Yes	Yes
Region	No	No	Yes
N	37172	37092	37172
R2	0.138	0.139	0.140
Adj. R2	0.137	0.137	0.137

Notes: t-values are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

The regression results, after addressing model endogeneity concerns, are displayed in Table 11. Notably, the coefficient of DCG_word, representing the extent of enterprise DT, remains significantly negative. This consistency in results underscores the robustness of our study's conclusions.

VII. FURTHER ANALYSIS

Furthermore, building on our previous analysis, increased auditor inputs may result in higher audit fees. To validate this, we examined the relationship between DT and audit fees. Table 12 shows that the DT coefficient is 3.174 (t = 15.49), indicating a significant rise in audit fees. While DT significantly increases audit fees for both Big Four and non-Big Four clients (3.073, t = 2.95; 3.391, t = 16.97, respectively), this pricing pattern reflects fundamentally different underlying mechanisms for each auditor type. For non-Big Four firms, the higher fee premium aligns with their greater increase in audit inputs (AuditLag β = 0.557***) and corresponding audit quality improvement (AbsDA β = -0.155***), suggesting a cost-plus pricing model where fees compensate for the substantial adaptation effort required to process clients' digital data. In contrast, Big Four auditors command fee premiums despite showing only marginal increases in audit inputs (AuditLag β = 0.655*) and no significant quality improvement, indicating their pricing power stems primarily from brand reputation and perceived value of auditing digitally transformed clients rather than actual cost increases or quality enhancements. This dichotomy supports an institutional perspective where non-Big Four firms operate through a resource-intensive, quality-focused adaptation model, while Big Four firms maintain a reputation-based premium pricing strategy that is less sensitive to either input adjustments or measurable quality changes from client digitalization.

TABLE 12. DT and AuditFee

	(1) AuditFee	(2) Big Four AuditFee	(3) Non-Big Four AuditFee
DCG_word	3.174***	3.073***	3.391***
	(15.49)	(2.95)	(16.97)
Size	0.350***	0.385***	0.312***
	(121.85)	(33.83)	(106.52)
Lev	0.168***	0.204***	0.204***
	(11.85)	(2.70)	(14.77)
BM	-0.109***	0.133*	-0.105***
	(-6.11)	(1.72)	(-5.97)
TobinQ	0.000	-0.018	-0.004
	(0.10)	(-1.31)	(-1.50)
Cashflow	0.076**	0.013	0.078**
	(2.23)	(0.08)	(2.33)
REC	0.192***	0.363***	0.192***
	(7.55)	(2.76)	(7.73)
INV	-0.170***	-0.420***	-0.128***
	(-7.57)	(-3.75)	(-5.81)
FIXED	-0.019	-0.418***	-0.008
	(-1.02)	(-5.16)	(-0.42)
TMTPay	0.083***	0.039**	0.070***
	(20.95)	(2.30)	(17.96)
Mshare	-0.000	-0.005***	0.000
	(-1.17)	(-5.26)	(0.99)
Balance	0.048***	0.142***	0.042***
	(13.45)	(7.76)	(12.05)
ListAge	-0.038***	-0.133***	-0.025***
	(-10.65)	(-7.93)	(-7.10)
Occupy	2.043***	0.819	2.042***
	(19.79)	(1.63)	(20.22)
Opinion	-0.174***	-0.096	-0.168***
	(-14.05)	(-1.20)	(-14.00)
Constant	4.874***	5.193***	5.812***
	(79.96)	(18.41)	(93.08)
Industry	Yes	Yes	Yes
Year	Yes	Yes	Yes
N	37172	1933	28133
R2	0.591	0.690	0.554
Adj. R2	0.590	0.679	0.553

Notes: t-values are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

VIII. CONCLUSION

In the era of digital economics, nations worldwide are formulating and implementing strategies to foster digital economic growth, recognizing big data and digital economy as crucial elements for prosperity and competitive edge. China, too, has prioritized digital economic development, introducing a series of supportive policies. To align with contemporary demands, Chinese enterprises are progressively undertaking DT. This technological shift is revolutionizing production and operational methodologies, reshaping competitive landscapes, and providing a novel endogenous impetus for corporate upgrading, restructuring, and high-quality development. However, this digital metamorphosis also introduces various risks that could potentially impact audit processes and quality. Consequently, it becomes imperative to evaluate whether auditors can accurately assess the audit risks associated with digitally transforming companies and maintain audit quality standards.

This study explores the impact of enterprise DT on audit quality and audit inputs, focusing on a sample of Shanghai and Shenzhen A-share listed companies from 2010 to 2023. Our results demonstrate that DT substantially improves audit quality, largely by strengthening internal controls and enhancing information disclosure transparency. However, these benefits require auditors to devote greater effort to manage the complexities arising from digital adoption, resulting in elevated audit fees. This dual impact is particularly evident among clients served by non-Big Four accounting firms.

Interestingly, the study highlights a growing digital divide within the audit profession. Non-Big Four firms, despite achieving higher audit quality through greater resource allocation, face rising costs that may undermine their competitive position. In contrast, Big Four firms, with their advanced technological infrastructure and established methodologies, are able to adapt to client DT more efficiently. This results in minimal observable changes in audit lag and quality metrics, not due to a lack of procedural adaptation, but because of their superior capacity to absorb complexity and manage risks effectively. This efficiency, coupled with their strong reputation, allows them to maintain fee premiums. This dichotomy underscores the challenges smaller audit firms face in adapting to DT, potentially exacerbating market inequalities.

The implications of this study extend beyond academia. For regulators, the results highlight the importance of fostering digital readiness among smaller audit firms to mitigate disparities. For audit firms, the findings underscore the necessity of balancing technological investments with cost management strategies. Policymakers should consider initiatives that promote digital literacy and resource-sharing to bridge the gap between large and small firms. Overall, our study contributes to the understanding of how DT reshapes audit practices, offering empirical evidence on its dualistic effects—enhancing quality while increasing costs. These insights are critical for stakeholders navigating the evolving landscape of the digital economy, where technology adoption is no longer optional but a strategic imperative.

This study has several limitations that provide avenues for future research. First, our measure of DT, based on keyword frequency in annual reports, reflects a firm's disclosed emphasis on digital initiatives. While this method is widely used and has been validated as a meaningful indicator of strategic orientation, it cannot fully distinguish between aspirational disclosure and the actual depth of technology implementation. Future research could benefit from more direct measures, such as IT capital expenditure, system implementation data, or survey-based adoption indicators, to capture the on-the-ground reality of DT. Second, this study employs the Big Four versus non-Big Four dichotomy as a proxy for audit firms' technological capabilities, which, while supported by prior literature and revealing a clear "digital divide" in outcomes, does not directly measure the audit firm's own level of DT (e.g., IT investment or digital maturity). The lack of publicly available, firm-level IT capability data for Chinese audit practices, particularly among non-Big Four firms, constrains a more granular analysis. Future research could advance this line of inquiry should such detailed data become accessible. Third, while we employed instrumental variables and other methods to mitigate endogeneity, we cannot completely rule out the possibility of omitted variable bias or reverse causality. The industry-average instruments, while theoretically sound and statistically strong, may not satisfy the exclusion restriction perfectly if unobserved industry-year shocks affect both digital adoption and audit outcomes. Therefore, the results should be interpreted as robust correlations that strongly support a causal narrative, but we caution against making definitive causal claims.

AUTHOR CONTRIBUTIONS

Yanan He: Conceptualization, Methodology, Writing Original Draft. Shuaifeng Li: Writing Review and Editing, Supervision, Resources, Funding Acquisition. Yifan Wu: Methodology, Data curation, Formal Analysis, Validation. Wen Li: Writing–Review and Editing, Project Administration, Investigation.

CONFLICTS OF INTEREST

The authors declare that there is no conflict of interest regarding the publication of this paper.

FUNDING

Shanghai Philosophy and Social Science Planning Project (Grant No. 2022ZJB002).

ACKNOWLEDGEMENTS

We sincerely thank the editors for their valuable comments and suggestions, which have significantly improved the manuscript. All authors have read and approved the final version of the manuscript.

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