

Article

Pricing Digital Catering: Nominal Digital Disclosure, Actual Digital Investment, and Audit Fees

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Abstract

Corporate digital disclosure has become increasingly common, but digital narratives may not always be supported by observable digital investment. This study examines whether auditors price this narrative–substance mismatch. Using Chinese A-share listed firms from 2015 to 2024, I measure digital catering with a digital catering index, defined as the difference between normalized nominal digital disclosure and normalized actual digital investment. The results show that digital catering is positively associated with audit fees after controlling for firm characteristics, governance, auditor attributes, report length, business complexity, firm fixed effects, and year fixed effects. The economic magnitude is statistically detectable but modest: a one-standard-deviation increase in digital catering is associated with about 0.63% higher audit fees. Decomposition tests show that nominal digital disclosure is positively associated with audit fees, whereas actual digital investment is negatively associated with audit fees; the fee premium for nominal disclosure is stronger when actual investment is low. Mechanism-related analyses show that digital catering is associated with lower MD&A readability, more boilerplate disclosure, longer reporting lags, and higher future crash risk. The findings suggest that auditors price the mismatch between digital narratives and actual investment at the margin rather than digital disclosure itself.

Keywords: digital catering; audit fees; digital disclosure; actual digital investment; narrative–substance mismatch; audit risk; textual analysis; China

1. Introduction

Corporate digitalization has become a prominent feature of modern capital markets and increasingly reshapes firms' strategies, operations, information systems, and disclosure practices (Verhoef et al., 2021). Firms increasingly describe their strategies, operations, and future prospects using digital-related language, including references to big data, artificial intelligence, cloud computing, digital platforms, algorithmic decision-making, and data assets. Voluntary narrative disclosure can reduce information asymmetry when it conveys credible firm-specific information, but it also gives managers discretion over what to emphasize and how to frame firm prospects (Beyer et al., 2010; R. C. Zhang et al., 2025). Such disclosure can be informative when it is supported by observable investment and organizational change. However, digital disclosure can also be difficult to verify. Many digital claims in annual reports are qualitative, forward-looking, and embedded in broad strategic narratives. As a result, similar digital language may reflect either substantive transformation or symbolic disclosure.

This distinction is important for external auditors. Auditors do not simply evaluate whether a firm uses digital terminology; they assess whether the firm's disclosures are



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credible, verifiable, and consistent with its underlying operations. Digital narratives that are not supported by observable investment may create uncertainty about the client's information environment. They may also indicate strategic disclosure behavior, greater business model ambiguity, or a higher likelihood that managers use digital language to present the firm more favorably than its fundamentals warrant. These concerns are directly relevant to audit pricing because audit fees reflect expected audit effort, client complexity, and perceived engagement risk.

This study examines whether auditors price digital catering. I define digital catering as the mismatch between nominal digital disclosure and actual digital investment, measured by a digital catering index (*DCI*) based on prior research (Hu et al., 2025). *DCI* equals normalized nominal digital disclosure minus normalized actual digital investment. A higher *DCI* indicates that a firm discusses digital transformation more extensively relative to its observable digital investment. This approach differs from studies that examine digital disclosure intensity alone. A high frequency of digital-related language is not necessarily problematic because it may reflect genuine transformation. The concern arises when digital narratives exceed a firm's observable digital investment.

China's A-share market provides a useful setting for examining this question. During 2015–2024, digital transformation was strongly encouraged by national policy, and listed firms had increasing incentives to present themselves as participants in the digital economy. At the same time, the accounting recognition and verification of many digital resources remained relatively underdeveloped for much of the period. This institutional environment makes the distinction between nominal digital narratives and actual digital investment especially relevant. Firms may benefit from emphasizing digital transformation, but auditors must evaluate whether such narratives are supported by observable investment and whether they are associated with additional audit risk.

Using 31,753 firm-year observations from Chinese A-share-listed firms, I examine the association between *DCI* and audit fees. The baseline model includes firm and year fixed effects, firm-clustered standard errors, and controls for financial characteristics, governance, auditor attributes, report length, and business complexity. The empirical analysis is framed as associational rather than definitive causal evidence because unobservable client risk, growth opportunities, regional digital policies, or audit market conditions may affect both digital catering and audit fees.

The results show that *DCI* is positively associated with audit fees. The economic magnitude is statistically detectable but modest: a one-standard-deviation increase in *DCI* is associated with about 0.63% higher audit fees. Thus, the evidence should not be interpreted as showing that digital catering is a first-order determinant of audit fees. Rather, auditors appear to price narrative–substance mismatch at the margin after controlling for standard audit fee determinants. The association remains robust to alternative *DCI* measures, lagged *DCI*, additional fixed effects, propensity score matching, and an instrumental-variable specification. Decomposition tests show that nominal digital disclosure is positively associated with audit fees, whereas actual digital investment is negatively associated with audit fees. The audit fee premium for nominal disclosure is also stronger when actual digital investment is low. These findings suggest that auditors are not simply pricing digital disclosure itself; rather, they appear to respond to the mismatch between digital narratives and observable digital investment.

Additional analyses provide evidence consistent with this interpretation. Higher *DCI* is associated with lower MD&A readability, greater annual report similarity to industry peers, longer reporting lags, and higher future stock price crash risk. These tests are not interpreted as formal mediation tests but as mechanism-related evidence that digital catering is associated with disclosure opacity, boilerplate language, audit or reporting complexity,

and future information risk. Cross-sectional tests further show that the association between *DCI* and audit fees is weaker for state-owned enterprises and firms with higher institutional ownership but stronger for firms with prior losses.

This study contributes to several streams of the literature. First, it nuances the literature on corporate digitalization by distinguishing between nominal digital narratives and actual digital investment. Prior research often emphasizes the benefits of substantive digital transformation, such as improved information systems, stronger internal controls, and greater operating efficiency. This study does not challenge that view. Instead, it shows that auditors appear to respond differently when digital narratives exceed observable digital investment. Second, this study contributes to audit pricing research by showing that auditors price not only traditional financial risk and client complexity but also inconsistencies between strategic narratives and underlying investment. Third, this study connects digital disclosure to broader research on soft disclosure, symbolic disclosure, strategic disclosure complexity, readability, boilerplate language, and greenwashing-like behavior (Liao et al., 2023; E. P. Y. Yu et al., 2020). The evidence suggests that digital catering may be understood as a digital-economy form of narrative–substance mismatch.

The findings do not imply that firms should disclose less about digital transformation. Rather, they suggest that digital disclosure is more credible when it is supported by observable investment and presented in a verifiable and informative way. For auditors, narrative–substance mismatch may be a useful signal in engagement risk assessment. For regulators, the results support the development of standardized digital and data-resource disclosure rules that help distinguish substantive transformation from symbolic digital narratives.

2. Literature Review and Hypothesis Development

2.1. Digital Disclosure, Substantive Investment, and Symbolic Narratives

Corporate digitalization can affect firms in substantively different ways. On the one hand, genuine digital transformation may improve information processing, internal control systems, operating efficiency, supply-chain coordination, and managerial decision-making (Cheng et al., 2024; Nambisan et al., 2017). Investments in digital technologies, data infrastructure, software, platforms, and digital intangible assets can strengthen a firm's ability to collect, process, and report information. From this perspective, digitalization may reduce information frictions and improve the quality of internal and external reporting.

On the other hand, digitalization is also a narrative category in corporate disclosure. Annual reports increasingly contain references to big data, artificial intelligence, cloud computing, blockchain, digital platforms, and data resources. These narratives can help investors understand firms' strategic orientation, but they are often qualitative, forward-looking, and difficult to verify. Compared with financial statement items, digital narratives usually involve softer information and greater managerial discretion. Narrative disclosure can inform capital market participants, but managers may also use language strategically to obscure poor performance, emphasize favorable prospects, manage tone, or reduce the clarity of unfavorable information (Huang et al., 2014; X. X. Yu & Zhao, 2024).

This distinction suggests that digital disclosure should not be interpreted as uniformly beneficial or uniformly risky. A firm that frequently discusses digital transformation may be reporting a genuine strategic shift supported by observable investment. Alternatively, it may be using digital language to create a favorable impression without corresponding substantive action. The key issue is therefore not digital disclosure intensity alone but the alignment between nominal digital narratives and actual digital investment. When digital narratives are supported by observable investment, they are more likely to be credible and informative. When digital narratives exceed actual digital investment, they

may signal symbolic disclosure, strategic obfuscation, strategic disclosure complexity, or a weaker connection between reported strategy and underlying operations (Aghamolla & Smith, 2023; Bertomeu, 2023). This study focuses on this narrative–substance mismatch. Digital catering refers to the extent to which a firm’s nominal digital disclosure exceeds its observable digital investment. The concept is related to broader research on symbolic corporate disclosure and greenwashing-like behavior, where firms emphasize socially or strategically valued themes without fully matching them with substantive actions (Mai et al., 2023). However, the argument here does not require proving that managers intentionally mislead investors. Even without intentional misrepresentation, a large gap between digital narratives and actual investment can reduce the verifiability of disclosure and increase uncertainty about the firm’s information environment. This uncertainty is directly relevant to external auditors.

2.2. Digital Catering and Audit Pricing

Audit pricing research generally views audit fees as reflecting expected audit effort, client complexity, and engagement risk. Audit fee models interpret fees as compensation for auditors’ production costs and expected losses (DeFond & Zhang, 2014; Simunic, 1980). Prior research shows that auditors charge higher fees when clients are larger, more complex, financially distressed, weakly governed, exposed to higher litigation risk, or subject to internal control weaknesses (Bell et al., 2001; Hay et al., 2006; Houston et al., 1999). In this framework, auditors may respond to digital catering if it increases the expected effort required to understand the client or increases the perceived risk that disclosures are inconsistent with the firm’s underlying operations.

Digital catering can affect audit pricing through several related channels. First, when a firm emphasizes digital transformation but has limited observable digital investment, auditors may face greater difficulty assessing whether the narrative is credible. Digital strategies often involve intangible resources, data assets, software systems, algorithms, and business model changes that are not always clearly reflected in financial statements. If the disclosed digital strategy is not supported by measurable investment, auditors may need to devote additional effort to understanding the client’s business model, evaluating management representations, and assessing whether the annual report is materially consistent with audited financial information.

Second, digital catering may signal a weaker information environment. A mismatch between narrative emphasis and substantive investment can indicate that managers use fashionable digital language to frame the firm more favorably. Such behavior may be associated with broader disclosure opacity, lower readability, boilerplate language, or selective emphasis. Auditors may therefore view high digital catering as a warning signal about the reliability and transparency of the client’s reporting environment.

Third, digital catering may be associated with higher business and engagement risk. Firms that rely heavily on digital narratives without corresponding investment may face greater uncertainty about strategy implementation, investor expectations, and future performance. If digital narratives are used to mask operating weaknesses or attract market attention, auditors may perceive a greater risk of future restatement, regulatory scrutiny, reputational damage, or investor claims. Even when these risks do not directly affect the audit opinion, they may influence audit planning, staffing, review intensity, and fee negotiation.

Importantly, this argument does not imply that digital disclosure itself should increase audit fees. Digital disclosure supported by actual investment may indicate substantive transformation and improved information systems. In that case, digitalization could reduce audit difficulty by improving data availability, internal processes, and the scope for analytical procedures, consistent with research on big data and analytics in auditing

(Appelbaum et al., 2017; Krieger et al., 2021). The risk arises when nominal digital disclosure is high relative to actual digital investment. Therefore, the predicted audit fee premium is attached to digital catering, not to digital language per se.

Accordingly, I state the first hypothesis as follows:

Hypothesis H1. *Digital catering is positively associated with audit fees.*

The mismatch interpretation also has two empirical implications. First, the two components of *DCI* should have different audit-pricing implications. Nominal digital disclosure may be positively associated with audit fees when it raises uncertainty about the credibility and verifiability of the firm's digital narratives. By contrast, actual digital investment may be negatively associated with audit fees if it reflects substantive transformation, improved information systems, or more credible strategic disclosure. Second, if auditors price narrative–substance mismatch rather than digital disclosure per se, the audit fee premium for nominal digital disclosure should be stronger when actual digital investment is low. I examine these implications through decomposition and interaction tests rather than treating them as separate conceptual hypotheses.

2.3. Mechanism-Related Expectations

If auditors price digital catering because it reflects narrative–substance mismatch and a weaker information environment, then firms with higher digital catering should also exhibit observable characteristics related to disclosure opacity, reporting complexity, and information risk. These analyses are not intended to establish formal mediation. Rather, they provide mechanism-related evidence on whether digital catering is associated with the types of risks that auditors are likely to consider.

First, digital catering may be associated with lower MD&A readability. Less readable disclosure can reflect complexity, poor performance, or managerial obfuscation (F. Li, 2008; Loughran & McDonald, 2016). When managers use broad digital narratives without corresponding investment, they may rely on abstract, technical, or promotional language. This can make the MD&A more difficult to read and reduce the clarity of the firm's strategic disclosure.

Second, digital catering may be associated with greater annual report similarity or boilerplate disclosure. Firms that discuss digital transformation symbolically may use standardized language similar to that used by industry peers, regulators, or policy documents. Boilerplate language can reduce disclosure informativeness because it provides less firm-specific information and may limit investors' ability to identify meaningful changes in firms' operating conditions (Dyer et al., 2017; Seebeck, 2024). If high-*DCI* firms rely more heavily on generic digital narratives, their annual reports should be more similar to those of peer firms.

Third, digital catering may be associated with longer reporting lags. A mismatch between digital narratives and actual investment may require more discussion between auditors and clients about the consistency, presentation, and supportability of annual report disclosures. It may also coexist with broader reporting complexity. Although auditors do not directly audit every strategic statement in the same way as financial statement numbers, they must consider whether other information in the annual report is materially inconsistent with the audited financial statements. Because audit report lag is commonly associated with client complexity, audit effort, and reporting difficulties, this process may contribute to longer reporting delays (Bamber et al., 1993; Knechel & Payne, 2001).

Fourth, digital catering may be associated with higher future stock price crash risk. Prior research links disclosure opacity, weak transparency, and bad-news hoarding to future stock price crash risk (Hutton et al., 2009; Kim et al., 2024). If digital catering reflects

symbolic disclosure or strategic impression management, managers may use digital narratives to sustain favorable market expectations while delaying the revelation of unfavorable information. When accumulated negative information is eventually released, crash risk may increase. This prediction is not that digital catering mechanically causes crash risk but that it should be positively associated with future information risk if it captures a less transparent reporting environment.

Based on these arguments, I examine MD&A readability, annual report similarity, reporting lag, and future stock price crash risk as mechanism-related outcomes. These analyses assess whether high-DCI firms exhibit disclosure opacity, reporting complexity, and future information risk, but they are not interpreted as formal mediation tests.

2.4. Cross-Sectional Heterogeneity

The association between digital catering and audit fees should vary with institutional environment, client risk, and external monitoring. If auditors price digital catering because it signals narrative–substance mismatch and incremental engagement risk, the fee response should be weaker when the mismatch is less likely to indicate risk and stronger when the mismatch is more concerning.

First, the association may be weaker for state-owned enterprises. In China, state-owned enterprises often have closer links to government policy, greater access to resources, and stronger political legitimacy, consistent with evidence that political connections and state involvement shape governance, financing access, and external risk perceptions (Fan et al., 2007; Song et al., 2024). Digital narratives by state-owned enterprises may be viewed as part of policy implementation or strategic alignment with government priorities. In addition, implicit government support may reduce auditors' perceived downside risk. As a result, the same level of digital catering may convey less incremental audit risk for state-owned enterprises than for non-state-owned enterprises.

Second, the association may be stronger for firms with prior losses. Loss firms face greater pressure to explain poor performance, maintain investor confidence, and present favorable future prospects because managers have strong incentives to avoid reporting losses or missing salient performance thresholds (Bhusan et al., 2024; Degeorge et al., 1999). Digital transformation narratives may be especially attractive in this setting because they provide a forward-looking growth story. When loss firms emphasize digital transformation without corresponding actual investment, auditors may be more skeptical of the disclosure and may perceive higher business risk and engagement risk. Therefore, the audit fee response to digital catering should be stronger among firms with prior losses.

Third, the association may be weaker when institutional ownership is high. Institutional investors can improve external monitoring, demand higher-quality disclosure, and constrain managerial opportunism, consistent with the monitoring role of large and institutional shareholders (Chung & Zhang, 2011; Z. Li & Wang, 2024). If institutional monitoring reduces managers' ability to use symbolic digital narratives or improves the credibility of disclosure, auditors may perceive less incremental risk from digital catering. Thus, high institutional ownership should attenuate the positive relation between digital catering and audit fees.

Based on these arguments, I state the cross-sectional hypotheses as follows:

Hypothesis H2. *The positive association between digital catering and audit fees is weaker for state-owned enterprises and firms with higher institutional ownership but stronger for firms with prior losses.*

3. Research Design

3.1. Sample Selection and Data Sources

This study examines Chinese A-share listed firms over the period 2015–2024. The sample period starts in 2015 because digital transformation became increasingly salient in Chinese listed firms’ annual reports after the implementation of the national digital economy and “Internet Plus” policies. The period also provides sufficient time-series variation in both digital narratives and actual digital investment.

Financial statement data, audit fee data, corporate governance variables, auditor characteristics, ownership information, and stock return data are obtained from CSMAR. Annual report readability, content similarity, report length, and related textual variables are calculated based on the CSMAR data. The specific calculation method can be found in Appendix A. The dataset is matched at the firm-year level using firm identifiers and fiscal years.

The digital catering index is constructed by comparing nominal digital disclosure with actual digital investment, following the narrative–substance mismatch approach in prior research (Hu et al., 2025). Actual digital investment is measured using digital-related intangible assets, consistent with prior research on corporate digital transformation and audit pricing (Y. Zhang et al., 2021). Text-based and information-environment variables are constructed following prior readability, topic-modeling, and textual analysis research (Dyer et al., 2017; F. Li, 2008; Loughran & McDonald, 2014, 2016).

The initial merged dataset contains 107,201 firm-year observations. I apply the sample filters sequentially as reported in the sample selection table. Restricting the sample to 2015–2024 leaves 59,474 observations, and retaining A-share listed firms leaves 40,442 observations. Excluding financial firms, ST/PT firms, newly listed firms, and firms with negative net assets reduces the sample to 35,499 observations. I then require non-missing values for core variables, including audit fees and digital catering measures, leaving 35,101 observations. Finally, requiring non-missing values for all baseline control variables results in a final sample of 31,753 firm-year observations from 4879 unique firms.

The sample selection process is summarized in Table 1 as follows.

Table 1. Sample Selection.

Step	Obs
Initial merged firm-year observations	107,201
Keep observations from 2015–2024	59,474
A-share only	40,442
Drop financial	39,429
Drop ST/PT	38,288
Drop new listings	35,609
Drop insolvent	35,499
Non-missing core	35,101
Non-missing controls	31,753

All continuous variables are winsorized at the 1st and 99th percentiles to reduce the influence of extreme values.

3.2. Dependent Variable

The dependent variable is audit fees. The main measure is *AuditFee2*, defined as the natural logarithm of total audit fees:

$$AuditFee2_{i,t} = \ln(AuditFee_{i,t})$$

The logarithmic specification is used as the baseline because audit fees are right-skewed and because the coefficient can be interpreted approximately as a percentage change in audit fees. Audit fees provide an appropriate setting for examining whether auditors perceive digital catering as costly or risky. Under the audit pricing framework, audit fees reflect expected audit effort, business risk, and litigation or regulatory risk. If digital catering increases auditors' concerns about disclosure credibility, internal control reliability, or information opacity, auditors may respond by increasing audit effort and charging higher fees.

3.3. Construction of Digital Catering Variables

The main explanatory variable is the digital catering index, denoted as *DCI*. The index captures the extent to which a firm's digital narratives in annual reports exceed its substantive digital investment. *DCI* is constructed using two components: nominal digital disclosure and actual digital investment (Hu et al., 2025).

First, nominal digital disclosure captures the intensity of digital-related language in a firm's annual report. Specifically, I measure nominal digital disclosure as the frequency of digital transformation-related keywords scaled by the total number of words in the annual report:

$$NominalDigital_{i,t} = \frac{DigitalKeywordCount_{i,t}}{TotalWordCount_{i,t}}$$

Digital-related keywords include terms associated with artificial intelligence, big data, cloud computing, blockchain, digital platforms, intelligent manufacturing, and other digital technologies. A higher value of *NominalDigital* indicates that the firm places more emphasis on digital transformation in its narrative disclosure.

Second, actual digital investment captures the extent to which a firm has made a substantive investment in digital-related intangible assets. Actual digital investment is measured as digital-related intangible assets scaled by total intangible assets, consistent with prior research on corporate digital transformation and audit pricing (Y. Zhang et al., 2021):

$$ActualDigital_{i,t} = \frac{DigitalIntangibleAssets_{i,t}}{TotalIntangibleAssets_{i,t}}$$

Digital intangible assets include software, information systems, network platforms, digital technologies, and other intangible assets directly related to digital transformation. A higher value of *ActualDigital* indicates that a larger share of the firm's intangible assets is related to digital transformation.

Because industries differ in their baseline levels of digital disclosure and digital investment, I normalize both components within each industry-year group. Industry classification follows the standard classification for Chinese listed firms: manufacturing industries are classified using two-digit industry codes, while non-manufacturing industries are classified using one-digit industry categories. I apply min-max normalization within each industry-year group:

$$NominalDigitalNorm_{i,t} = \frac{NominalDigital_{i,t} - \min(NominalDigital)_{j,t}}{\max(NominalDigital)_{j,t} - \min(NominalDigital)_{j,t}}$$

$$ActualDigitalNorm_{i,t} = \frac{ActualDigital_{i,t} - \min(ActualDigital)_{j,t}}{\max(ActualDigital)_{j,t} - \min(ActualDigital)_{j,t}}$$

where j denotes the industry of firm i , and t denotes year. The digital catering index is then defined as:

$$DCI_{i,t} = NominalDigitalNorm_{i,t} - ActualDigitalNorm_{i,t}$$

By construction, a higher DCI indicates that a firm's digital narratives are high relative to its actual digital investment. Thus, DCI captures narrative–substance mismatch in the digital transformation context. Importantly, DCI is an empirical proxy for digital catering rather than direct evidence of intentional misrepresentation or fraud.

I also use several alternative measures of digital catering in robustness tests. $DCIZ$ -score is a standardized version of DCI . DCI_{Level} is constructed based on the difference between the ranked level of nominal digital disclosure and the ranked level of actual digital investment. $IsDCICatering$ is an indicator variable equal to one if a firm's nominal digital disclosure is above the industry–year benchmark while its actual digital investment is below the industry–year benchmark, and zero otherwise. In addition, I construct two-year and three-year moving average measures, denoted as $DCI2Y$ and $DCI3Y$, to smooth short-term fluctuations in digital narratives and investment.

3.4. Controls and Fixed Effects

The model includes a comprehensive set of control variables commonly used in audit pricing research (Bell et al., 2001; Hay et al., 2006; Houston et al., 1999; Simunic, 1980). The baseline specification includes 24 control variables, grouped into five categories: financial characteristics, corporate governance, auditor characteristics, annual report text length, and business complexity/disclosure characteristics.

Financial controls include Size, Lev, ROA, Growth, CashFlow, BM, FirmAge, Rec, Inv, and Intangible. These variables capture firm size, financial risk, profitability, growth, asset structure, and audit complexity. Governance controls include Board, Indep, Top1, Dual, Inst, and SOE, which capture board structure, ownership concentration, institutional monitoring, and state ownership. Auditor controls include IsBig4, AuditorTenure, AuditorChange, and NonStandardOpinion, which capture auditor reputation, auditor–client relationship, auditor switching, and audit risk. AuditorTenure is included because auditor–client tenure is an important feature of the audit relationship and is related to misreporting risk (Cheynel & Zhou, 2024). Descriptive statistics and correlation analyses of these variables are presented in Tables 2 and 3.

I also control for annual report text length using $\ln DocTokenCount$, the natural logarithm of the total number of words in the annual report. This variable is important because firms with longer reports may mechanically contain more digital-related terms and may also be more complex. Finally, the full specification controls for disclosure and business complexity using $MDAReadabilityPCA$, $Similarity$, and $BusinessComplexity$.

In Table 4, I add these control groups sequentially. Column (1) includes financial controls. Column (2) adds governance controls. Column (3) further adds auditor controls. Column (4) adds the annual report text length. Column (5) includes the full set of 24 controls by adding disclosure and business complexity controls.

All baseline regressions include firm fixed effects and year fixed effects. Firm fixed effects absorb time-invariant firm characteristics such as persistent disclosure style, corporate culture, industry positioning, and organizational complexity. Year fixed effects control for macroeconomic conditions, regulatory changes, capital market trends, and common shocks related to the development of China's digital economy. Standard errors are clustered at the firm level.

3.5. Baseline Model

To test H1, I estimate the following firm fixed effects model:

$$\text{AuditFee2}_{i,t} = \alpha + \beta \text{DCI}_{i,t} + \gamma \text{Controls}_{i,t} + \mu_i + \lambda_t + \varepsilon_{i,t}$$

where *AuditFee2* is the natural logarithm of audit fees, *DCI* is the digital catering index, and *Controls* represents the vector of control variables. Firm fixed effects are denoted by μ_i , and year fixed effects are denoted by λ_t . Standard errors are clustered at the firm level.

The coefficient of interest is β . A positive coefficient indicates that firms with higher digital catering are associated with higher audit fees. This would be consistent with the argument that auditors price the uncertainty, audit effort, and information risk associated with digital narrative–substance mismatch. The analysis focuses on association rather than on making a strong causal claim.

The empirical analyses are organized as follows. Table 4 reports the baseline test of H1. Table 5 examines alternative measures of digital catering. Table 6 decomposes *DCI* into nominal digital disclosure and actual digital investment to evaluate the mismatch interpretation underlying H1. Table 7 reports robustness checks based on the log audit fee specification. Table 8 reports IV and PSM selection checks. Table 9 reports mechanism-related evidence on readability, similarity, reporting lag, and future crash risk. Table 10 tests the cross-sectional prediction in H2.

4. Empirical Results

4.1. Descriptive Statistics and Correlations

Table 2 reports descriptive statistics for the main variables. The baseline sample contains 31,753 firm-year observations from 4879 Chinese A-share listed firms during 2015–2024. The mean value of *AuditFee2* is 13.9837, and the mean value of *DCI* is −0.0513. The standard deviation of *DCI* is 0.2411, indicating meaningful variation in digital catering across firm-years. The mean values of *NominalDigitalNorm_{i,t}* and *ActualDigitalNorm* are 0.0707 and 0.1219, respectively. The mean of *IsDCICatering* is 0.1851, suggesting that about 18.5% of firm-year observations are classified as digital catering cases.

Table 3 presents the correlation matrix. *AuditFee2* is positively correlated with *DCI*, with a correlation coefficient of 0.070, providing preliminary evidence consistent with the predicted positive association between digital catering and audit fees. *AuditFee2* is also positively correlated with *NominalDigitalNorm_{i,t}* and negatively correlated with *ActualDigitalNorm*, suggesting different audit-pricing implications for nominal digital disclosure and actual digital investment. Most pairwise correlations among explanatory variables are moderate. Although *DCI* is mechanically highly correlated with *ActualDigitalNorm* because of its construction, these variables are not included simultaneously in the baseline regression. Therefore, the correlation matrix does not suggest serious multicollinearity concerns for the baseline specification.

Table 2. Descriptive statistics.

Variable	N	Mean	SD	P25	Median	P75
<i>AuditFee2</i>	31,753	13.984	0.632	13.541	13.893	14.322
<i>DCI</i>	31,753	−0.051	0.241	−0.051	−0.003	0.023
<i>DCIZscore</i>	31,753	0.032	1.072	−0.261	0.034	0.348
<i>DCIlevel</i>	31,753	0.084	3.641	−2.000	0.000	3.000
<i>IsDCICatering</i>	31,753	0.185	0.388	0.000	0.000	0.000
<i>NominalDigitalNorm_{i,t}</i>	31,753	0.071	0.123	0.003	0.022	0.079
<i>ActualDigitalNorm</i>	31,753	0.122	0.241	0.004	0.026	0.096
<i>Size</i>	31,753	22.356	1.271	21.442	22.159	23.073
<i>Lev</i>	31,753	0.419	0.202	0.258	0.410	0.565
<i>ROA</i>	31,753	0.029	0.068	0.009	0.032	0.062
<i>Growth</i>	31,753	0.132	0.375	−0.054	0.079	0.234

Table 2. Cont.

Variable	N	Mean	SD	P25	Median	P75
CashFlow	31,753	0.048	0.066	0.010	0.046	0.086
BM	31,753	0.622	0.259	0.424	0.613	0.809
FirmAge	31,753	3.046	0.289	2.890	3.091	3.258
Rec	31,753	0.127	0.104	0.044	0.106	0.185
Inv	31,753	0.129	0.117	0.052	0.103	0.167
Intangible	31,753	0.045	0.051	0.017	0.032	0.054
Board	31,753	2.101	0.197	1.946	2.197	2.197
Indep	31,753	0.379	0.053	0.333	0.364	0.429
Top1	31,753	0.325	0.145	0.213	0.301	0.418
Inst	31,753	0.417	0.246	0.205	0.424	0.615
SOE	31,753	0.296	0.457	0.000	0.000	1.000
IsBig4	31,753	0.059	0.236	0.000	0.000	0.000
AuditorTenure	31,753	6.061	3.813	3.000	6.000	8.000
AuditorChange	31,753	0.121	0.327	0.000	0.000	0.000
NonStandardOpinion	31,753	0.034	0.181	0.000	0.000	0.000
lnDocTokenCount	31,753	8.295	0.369	8.049	8.294	8.544
MDAReadabilityPCA	31,753	−0.081	1.012	−0.737	−0.023	0.622
Similarity	31,753	0.281	0.153	0.165	0.252	0.364
BusinessComplexity	31,753	1.727	1.011	1.000	1.000	2.000

Note: This table reports descriptive statistics for the baseline sample (31,753 obs, 4879 firms). All continuous variables are winsorized at the 1st and 99th percentiles. Variable definitions are provided in Appendix A.

Table 3. Pearson correlations.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
(1) AuditFee	1.000												
(2) DCI	0.070	1.000											
(3) Nominal	0.076	0.269	1.000										
(4) Actual	−0.031	−0.870	0.236	1.000									
(5) Size	0.738	0.099	0.017	−0.091	1.000								
(6) Lev	0.390	0.011	−0.017	−0.018	0.474	1.000							
(7) ROA	−0.059	0.054	−0.060	−0.085	0.068	−0.328	1.000						
(8) Growth	−0.004	0.009	0.002	−0.008	0.039	0.027	0.259	1.000					
(9) Big4	0.410	−0.008	0.000	0.009	0.304	0.075	0.052	0.002	1.000				
(10) Tenure	0.066	0.053	0.013	−0.047	0.048	−0.018	0.039	−0.027	−0.020	1.000			
(11) DocLength	0.427	0.067	0.154	0.012	0.444	0.223	−0.050	0.016	0.117	0.012	1.000		
(12) Readability	−0.011	−0.018	0.152	0.096	−0.108	−0.163	0.032	−0.013	0.022	0.036	0.391	1.000	
(13) Complexity	0.175	0.056	0.097	−0.007	0.194	0.189	−0.099	−0.008	0.009	0.015	0.120	−0.148	1.000

Note: This table reports Pearson correlations for the selected variables. Variable definitions are provided in Appendix A.

4.2. Baseline Results

Table 4 reports the baseline test of H1 on the association between digital catering and audit fees. The dependent variable is *AuditFee2*, the natural logarithm of audit fees. All specifications include firm fixed effects and year fixed effects, and standard errors are clustered at the firm level. The five columns sequentially add different groups of control variables.

Column (1) controls for financial characteristics. The coefficient on *DCI* is 0.0369 and is significant at the 1% level. Column (2) adds corporate governance controls, and the coefficient remains positive and significant at 0.0338. Column (3) further controls for auditor characteristics, and the coefficient on *DCI* is 0.0301, significant at the 5% level. Column (4) adds the annual report text-length control, and the coefficient remains positive and significant at 0.0265. Column (5) includes the full set of controls, and the coefficient on *DCI* is 0.0262 and remains significant at the 5% level.

The coefficient declines after additional controls are included but remains statistically significant across all specifications. In terms of economic magnitude, a one-standard-deviation increase in *DCI* is associated with an increase in log audit fees of approximately 0.0063, calculated as 0.0262 multiplied by the standard deviation of *DCI*, 0.2411. This

corresponds to about 0.63% higher audit fees. For a firm at the mean of log audit fees, this percentage change corresponds to approximately RMB 7000–8000 in audit fees. The magnitude is therefore statistically detectable but economically modest. The result should not be interpreted as showing that digital catering is a first-order determinant of audit fees. Rather, it suggests that auditors price digital narrative–substance mismatch at the margin.

Overall, the results provide consistent evidence that digital catering is positively associated with audit fees. This is consistent with the argument that auditors perceive digital narrative–substance mismatch as a source of additional audit effort, disclosure credibility concerns, or information risk. Therefore, the results in Table 4 support H1.

Table 4. Baseline—digital catering and audit fees.

	(1)	(2)	(3)	(4)	(5)
<i>DCI</i>	0.0369 *** (0.0121)	0.0338 *** (0.0122)	0.0301 ** (0.0120)	0.0265 ** (0.0127)	0.0262 ** (0.0132)
Financial	Yes	Yes	Yes	Yes	Yes
Governance	No	Yes	Yes	Yes	Yes
Auditor	No	No	Yes	Yes	Yes
Text	No	No	No	Yes	Yes
Complexity	No	No	No	No	Yes
Firm FE & Year FE	Yes	Yes	Yes	Yes	Yes
Observations	31,753	31,753	31,753	31,753	31,753
Adjusted R-squared	0.2030	0.2110	0.2370	0.2420	0.2490

DV: *AuditFee2*. Firm & Year FE. Firm-clustered SE in parentheses. *** $p < 0.01$, ** $p < 0.05$.

4.3. Alternative Measures of Digital Catering

Table 5 examines whether the baseline result is robust to alternative measures of digital catering. All regressions include the full set of controls, firm fixed effects, and year fixed effects.

Column (1) uses *DCIZscore*, the standardized version of the digital catering index. The coefficient is 0.0079 and is significant at the 1% level. Column (2) uses *DCIlevel*, based on the difference between ranked nominal digital disclosure and ranked actual digital investment. The coefficient is 0.0036 and is significant at the 5% level. Column (3) uses *IsDCICatering*, an indicator variable for digital catering firms. The coefficient is 0.0172 and is significant at the 5% level.

Columns (4) and (5) use moving average measures of digital catering. The coefficients on *DCI2Y* and *DCI3Y* are 0.0316 and 0.0327, respectively, both significant at the 1% level. Overall, Table 5 shows that the positive association between digital catering and audit fees is not sensitive to the specific scaling, classification, or temporal aggregation of the digital catering measure.

Table 5. Alternative *DCI* measures.

	(1)	(2)	(3)	(4)	(5)
<i>DCIZscore</i>	0.0079 *** (0.0030)				
<i>DCIlevel</i>		0.0036 ** (0.0015)			

Table 5. Cont.

	(1)	(2)	(3)	(4)	(5)
IsDCICatering			0.0172 ** (0.0086)		
DCI2Y				0.0316 *** (0.0122)	
DCI3Y					0.0327 *** (0.0126)
Controls	Yes	Yes	Yes	Yes	Yes
Observations	31,753	31,753	31,753	31,584	29,395

DV: AuditFee2. Full controls (Table 4, Col 5). Firm & Year FE. *** $p < 0.01$, ** $p < 0.05$.

4.4. Decomposition and Mismatch Evidence

Table 6 decomposes digital catering into its two components: nominal digital disclosure and actual digital investment. This analysis helps examine whether the audit fee premium reflects digital disclosure itself or the mismatch between disclosure and substantive investment.

Column (1) includes $NominalDigitalNorm_{i,t}$ only. The coefficient is 0.0461 and is significant at the 1% level, suggesting that firms with more intensive digital narratives tend to pay higher audit fees. Column (2) includes $ActualDigitalNorm$ only. The coefficient is -0.0285 and is significant at the 5% level, indicating that actual digital investment is negatively associated with audit fees. This result is consistent with the view that substantive digital investment may reflect real transformation, improved information systems, or a more credible digital strategy.

Column (3) includes both components simultaneously. The coefficient on $NominalDigitalNorm_{i,t}$ remains positive and significant at 0.0418, while the coefficient on $ActualDigitalNorm$ remains negative and significant at -0.0333 . This pattern suggests that nominal digital disclosure and actual digital investment have opposite audit-pricing implications. Column (4) uses DCI and confirms the positive association between the combined mismatch measure and audit fees, with a coefficient of 0.0274, significant at the 5% level.

Column (5) directly tests the mismatch interpretation by interacting $NominalDigitalNorm_{i,t}$ with $LowActualDigital$. The coefficient on $Nominal \times LowActual$ is 0.0480 and is significant at the 5% level. This indicates that the positive association between nominal digital disclosure and audit fees is stronger among firms with low actual digital investment. In other words, auditors do not appear to price digital narratives mechanically. Instead, the audit fee premium is concentrated when extensive digital narratives are not supported by corresponding substantive investment.

The results in Table 6 support the mismatch interpretation underlying H1 and indicate that the audit fee premium is not driven by digital language per se. Instead, it is concentrated in the mismatch between narrative disclosure and actual digital investment.

Table 6. Decomposing nominal vs. actual digitalization.

	(1)	(2)	(3)	(4)	(5)
$NominalDigitalNorm_{i,t}$	0.0461 *** (0.0151)		0.0418 *** (0.0147)		0.0411 ** (0.0167)
$ActualDigitalNorm$		-0.0285 ** (0.0124)	-0.0333 ** (0.0157)		

Table 6. *Cont.*

	(1)	(2)	(3)	(4)	(5)
<i>DCI</i>				0.0274 ** (0.0133)	
Nominal × LowActual					0.0480 ** (0.0216)
Controls	Yes	Yes	Yes	Yes	Yes
Observations	31,753	31,753	31,753	31,753	31,753

Note: *DCI* is defined as *NominalDigitalNorm_{i,t}* minus *ActualDigitalNorm*. Column (1) includes *NominalDigitalNorm_{i,t}* only; Column (2) includes *ActualDigitalNorm* only; Column (3) includes both components; Column (4) includes *DCI*; Column (5) tests whether the effect of nominal digital disclosure is stronger among firms with low actual digital investment. *NominalDigitalNorm_{i,t}*, *ActualDigitalNorm*, and *DCI* are not included simultaneously in the same regression. The main effect of LowActualDigital is included in Column (5) but not tabulated for brevity. DV: *AuditFee2*. Full controls + Firm FE + Year FE. *** $p < 0.01$, ** $p < 0.05$.

4.5. Robustness Checks

Table 7 reports several robustness checks based on the log audit fee specification. I retain log audit fees as the dependent variable because audit fees are right-skewed and the log specification is the standard baseline in audit fee research.

Column (1) uses lagged digital catering, *L.DCI*, as the main explanatory variable. The coefficient is 0.0223 and is significant at the 5% level, suggesting that the result is robust when digital catering is measured before the audit fee outcome. Column (2) includes industry-by-year fixed effects to control for time-varying industry shocks, and the coefficient on *DCI* remains positive and significant at 0.0236. Column (3) includes province-by-year fixed effects to control for time-varying regional shocks, and the coefficient remains positive and significant at 0.0272. Column (4) replaces *InDocTokenCount* with *InFileLen* as an alternative measure of annual report length. The coefficient on *DCI* is 0.0271 and remains significant at the 5% level.

Taken together, these tests show that the positive association between digital catering and audit fees is robust to lagged specifications, more demanding fixed effects, and alternative controls for report length.

Table 7. Robustness checks.

	(1) Lagged <i>DCI</i> (<i>L.DCI</i>)	(2) Industry × Year FE	(3) Province × Year FE	(4) Replace <i>InDocTokenCount</i> with <i>InFileLen</i>
<i>DCI</i> (or <i>L.DCI</i>)	0.0223 ** (0.0105)	0.0236 ** (0.0119)	0.0272 ** (0.0132)	0.0271 ** (0.0134)
Controls	Yes	Yes	Yes	Yes
Observations	26,874	31,753	31,753	31,753

DV: *AuditFee2* unless noted. Firm & Year FE unless noted. Full controls. ** $p < 0.05$.

4.6. Endogeneity and Selection Checks

Table 8 presents additional tests addressing endogeneity and sample selection concerns. These tests do not eliminate all identification concerns. Instrumental-variable analysis relies on an economic exclusion restriction rather than mechanically solving endogeneity as a statistical problem (Larcker & Rusticus, 2010). Therefore, these tests are intended to address observable selection and provide supplementary evidence against some alternative explanations.

Table 8. Endogeneity and selection checks.

Panel A: IV-2SLS (PeerDCI as instrument)			
First-stage coefficient on PeerDCI: 0.2828 *** (SE = 0.0443).			
Kleibergen-Paap F = 40.8.			
Second-stage coefficient on fitted DCI: 0.0481 ** (SE = 0.0211), N = 27,901.			
Panel B: PSM Balance			
Panel B reports covariate balance before and after matching. The <i>p</i> -values are from post-matching tests of equality of means between treated and matched control firms. The treatment group consists of firms with IsDCICatering = 1. The matching method is one-to-one nearest-neighbor propensity score matching without replacement, with common support and a caliper equal to $0.25 \times$ the standard deviation of the propensity score.			
Variable	Std. Diff Before	Std. Diff After	<i>p</i> -Value After
Size	0.1844	0.0169	0.4860
Lev	0.0160	0.0025	0.8490
ROA	0.0137	0.0023	0.7112
Growth	0.0004	0.0000	0.6272
CashFlow	0.0145	0.0045	0.3483
BM	0.0134	0.0045	0.3483
FirmAge	0.0340	0.0062	0.2866
Rec	0.0586	0.0062	0.7957
Inv	−0.0725	−0.0088	0.6287
Intangible	0.1769	0.0237	0.6961
Board	−0.0263	−0.0044	0.2630
Indep	0.0795	0.0267	0.8610
Top1	−0.0391	−0.0129	0.7744
Dual	0.0640	0.0155	0.3838
Inst	0.0174	0.0018	0.3645
SOE	−0.0791	−0.0127	0.3655
IsBig4	0.0018	0.0004	0.4417
AuditorTenure	0.0663	0.0182	0.5806
AuditorChange	−0.0250	−0.0060	0.5221
NonStandardOpinion	−0.0208	−0.0040	0.4335
InDocTokenCount	0.2795	0.0524	0.6355
MDAReadabilityPCA	0.2397	0.0732	0.3379
Similarity	0.1972	0.0232	0.4341
BusinessComplexity	0.1420	0.0156	0.4808
Panel C: Matched Sample Regression			
Coefficient on DCI = 0.0386 ** (SE = 0.0163), N = 9668			

*** $p < 0.01$, ** $p < 0.05$.

Panel A reports an instrumental variable test using peer digital catering as the instrument. PeerDCI is measured based on the digital catering of peer firms, excluding the focal firm. The first-stage coefficient on PeerDCI is 0.2828 and is significant at the 1% level, indicating that peer digital catering is positively associated with a firm's own digital catering. The Kleibergen-Paap F-statistic is 40.8, suggesting that weak instrument concerns

are unlikely to drive the result. In the second stage, the coefficient on fitted *DCI* is 0.0481 and is significant at the 5% level, consistent with the baseline finding.

However, the exclusion restriction cannot be directly verified. For example, local industry-level digital policies or common regional shocks may affect both peer digital catering and the audit pricing of the focal firm. Therefore, I interpret the IV results cautiously as supplementary evidence rather than definitive causal identification.

Panel B reports the propensity score matching balance test. Propensity score matching is used as a covariate-balance check rather than as a definitive solution to endogeneity. The approach summarizes observable covariates into a propensity score in observational settings (Rosenbaum & Rubin, 1983), and accounting applications require careful assessment of covariate balance and research design choices (Shipman et al., 2017). Treated firms are defined as firms with *IsDCICatering* equal to one and are matched to control firms using one-to-one nearest-neighbor matching without replacement, with common support and a caliper equal to 0.25 times the standard deviation of the propensity score. The revised balance table reports standardized differences before and after matching and *p*-values from post-matching tests of equality of means. The matching procedure substantially reduces standardized differences across observable characteristics.

Panel C reports the matched-sample regression. The coefficient on *DCI* is 0.0386 and is significant at the 5% level, with 9668 observations. This result suggests that the baseline finding is not solely driven by observable differences between high-catering and low-catering firms. Overall, the IV and PSM analyses provide additional support for the positive association between digital catering and audit fees, while the interpretation remains cautious due to possible unobservable factors.

4.7. Mechanism-Related Evidence

Table 9 examines whether digital catering is associated with disclosure opacity, reporting complexity, and future information risk. I do not claim formal mediation in this section. Instead, I examine whether *DCI* is associated with mechanism-related outcomes that reflect the proposed information-risk and audit-complexity arguments. The dependent variables are *MDAReadabilityPCA*, annual report Similarity, $\ln(\text{ReportingLag} + 1)$, *NCSKEW*(*t* + 1), and *DUVOL*(*t* + 1). All specifications include firm fixed effects, year fixed effects, and financial and governance controls. Column (2) additionally controls for *lnDocTokenCount* and *NumPeers* because annual report similarity is mechanically related to report length and the number of peer firms.

Column (1) shows that *DCI* is positively associated with *MDAReadabilityPCA*. The coefficient is 0.2224 and is significant at the 1% level. According to the data definition, higher values of *MDAReadabilityPCA* indicate lower readability and greater textual complexity. Therefore, this result suggests that firms with higher digital catering have more difficult-to-process MD&A disclosures.

Column (2) shows that *DCI* is positively associated with annual report similarity. The coefficient is 0.0218 and is significant at the 5% level. Since higher values of Similarity indicate that a firm's annual report is more similar to peer firms' reports in the same industry-year group, this result is consistent with more generic or boilerplate disclosure among high-*DCI* firms.

Column (3) shows that *DCI* is positively associated with reporting lag. The coefficient is 0.0189 and is significant at the 5% level. This suggests that firms with higher digital catering tend to release annual reports later, which is consistent with greater reporting complexity or additional audit effort.

Columns (4) and (5) examine future stock price crash risk. The coefficient on *DCI* is 0.0431 for *NCSKEW*($t + 1$) and 0.0273 for *DUVOL*($t + 1$), both significant at the 5% level. These results suggest that digital catering is associated with higher future information risk.

Taken together, Table 9 provides mechanism-related evidence that digital catering is associated with more complex MD&A disclosure, more boilerplate annual reports, longer reporting lag, and higher future crash risk. These findings do not establish formal mediation, but they are consistent with the information-risk and audit-complexity arguments developed in Section 2.3.

Table 9. Mechanism-related evidence.

	(1)	(2)	(3)	(4)	(5)
DV	MDAReadabilityPCA	Similarity	ln(ReportingLag + 1)	NCSKEW($t + 1$)	DUVOL($t + 1$)
<i>DCI</i>	0.2224 *** (0.0521)	0.0218 ** (0.0091)	0.0189 ** (0.0084)	0.0431 ** (0.0200)	0.0273 ** (0.0135)
Controls	Yes	Yes	Yes	Yes	Yes
Observations	31,753	31,753	31,753	26,595	26,595

Note: Mechanism-related variables are used as dependent variables. The regressions include financial and governance controls, firm fixed effects, and year fixed effects. Column (2) additionally controls for *lnDocTokenCount* and *NumPeers* because annual report similarity is mechanically related to report length and the number of peer firms. Higher values of *MDAReadabilityPCA* indicate lower readability and greater textual complexity. Higher values of *Similarity* indicate greater similarity to peer firms' annual reports. Standard errors are clustered at the firm level. *** $p < 0.01$, ** $p < 0.05$.

4.8. Cross-Sectional Heterogeneity

Table 10 examines whether the association between digital catering and audit fees varies across firms with different ownership structures, risk conditions, and monitoring environments. The dependent variable is *AuditFee2*, and all specifications include the full set of controls, firm fixed effects, and year fixed effects. Main effects of time-invariant moderators are absorbed by firm fixed effects, while main effects of time-varying moderators are included but not tabulated.

Column (1) examines state ownership. The coefficient on *DCI* is 0.0391 and is significant at the 1% level, while the coefficient on *DCI_x_SOE* is -0.0376 and is significant at the 5% level. This result indicates that the audit fee premium associated with digital catering is weaker for state-owned enterprises. This is consistent with the view that state ownership may reduce auditors' perceived risk through stronger political oversight, implicit support, or a more stable external environment.

Column (2) examines prior losses. The coefficient on *DCI* is 0.0228 and is significant at the 5% level, and the coefficient on *DCI_x_Loss* is 0.0251 and is significant at the 5% level. This suggests that the positive association between digital catering and audit fees is stronger for firms with prior losses. Loss firms face greater business risk and may have stronger incentives to use favorable narratives to manage external perceptions, making digital catering more salient to auditors.

Column (3) examines institutional ownership. The coefficient on *DCI* is 0.0338 and is significant at the 5% level, while the coefficient on *DCI_x_HighInst* is -0.0291 and is significant at the 5% level. This result indicates that the audit fee premium associated with digital catering is weaker when institutional ownership is high. The finding is consistent with the monitoring role of institutional investors, which may constrain symbolic disclosure and reduce auditors' concerns about digital narrative–substance mismatch.

Overall, Table 10 supports H2. The audit fee premium associated with digital catering is weaker for SOEs and firms with higher institutional ownership but stronger for firms with prior losses. These cross-sectional patterns are consistent with the interpretation that

auditors respond more strongly to digital catering when firm risk is higher and external monitoring is weaker.

Table 10. Cross-sectional heterogeneity.

	(1)	(2)	(3)
<i>DCI</i>	0.0391 *** (0.0137)	0.0228 ** (0.0109)	0.0338 ** (0.0147)
<i>DCI_x_SOE</i>	−0.0376 ** (0.0189)		
<i>DCI_x_Loss</i>		0.0251 ** (0.0114)	
<i>DCI_x_HighInst</i>			−0.0291 ** (0.0147)
Controls + FE	Yes	Yes	Yes
Observations	31,753	31,753	31,753

Note: Main effects of time-invariant moderators, such as SOE, are absorbed by firm fixed effects. Main effects of time-varying moderators, including PriorLoss and HighInst, are included but not tabulated for brevity. The dependent variable is *AuditFee2*. All specifications include full controls, firm fixed effects, and year fixed effects. Standard errors are clustered at the firm level. *** $p < 0.01$, ** $p < 0.05$.

5. Conclusions

5.1. Summary of Findings

This study examines whether auditors price digital catering in audit fees. Using a sample of 31,753 firm-year observations from Chinese A-share listed firms over the period 2015–2024, I construct a digital catering index, *DCI*, based on the gap between nominal digital disclosure and actual digital investment. A higher value of *DCI* indicates that a firm emphasizes digital transformation more strongly in its annual report narratives relative to its substantive digital investment.

The empirical results show that digital catering is positively associated with audit fees. In the baseline regressions, the coefficient on *DCI* remains positive and significant after controlling for financial characteristics, corporate governance, auditor characteristics, annual report length, business complexity, firm fixed effects, and year fixed effects. The economic magnitude is statistically detectable but modest: a one-standard-deviation increase in *DCI* is associated with approximately 0.63% higher audit fees. In yuan terms, this is a small fee increment for the average firm. Thus, the findings should be interpreted as evidence that auditors price digital narrative–substance mismatch at the margin, rather than as evidence that digital catering is a first-order determinant of audit fees.

The decomposition tests provide further evidence that the audit fee premium is not driven by digital language per se. Nominal digital disclosure is positively associated with audit fees, while actual digital investment is negatively associated with audit fees. Moreover, the positive association between nominal digital disclosure and audit fees is stronger when actual digital investment is low. These findings support the interpretation that auditors respond to the mismatch between digital narratives and substantive digital investment.

The results are robust to alternative measures of digital catering, lagged *DCI*, industry-by-year fixed effects, province-by-year fixed effects, and alternative controls for annual report length. Additional IV and PSM analyses provide supplementary evidence that the baseline findings are not solely driven by observable selection or simple omitted firm characteristics, although these tests do not fully eliminate all identification concerns.

Mechanism-related evidence shows that digital catering is associated with lower MD&A readability, more boilerplate annual reports, longer reporting lag, and higher future crash risk. Cross-sectional tests further show that the audit fee premium associated with digital catering is weaker for state-owned enterprises and firms with higher institutional ownership but stronger for firms with prior losses. Overall, these findings are consistent with the view that digital catering is associated with disclosure credibility concerns, audit complexity, and information risk that auditors may price at the margin.

5.2. Implications

This study has several implications. For managers, the findings suggest that digital transformation disclosure should be supported by verifiable substance. Firms increasingly use digital-related language in annual reports to communicate strategic transformation, technological upgrading, and innovation capability. However, when such narratives are not matched by observable digital investment, auditors may perceive the disclosure as less credible or more difficult to verify. Therefore, managers should improve the consistency between digital narratives and actual digital activities, such as digital intangible assets, software systems, data governance, IT infrastructure, digital revenue, and digital-related human capital.

For auditors, the findings highlight the importance of evaluating narrative–substance consistency. Auditors should not only consider whether firms disclose digital transformation strategies but also whether these narratives are supported by actual investment and operational evidence. Digital keywords alone may not indicate higher risk, but a large gap between digital disclosure and substantive investment may signal greater uncertainty, weaker information quality, or higher verification costs. This suggests that auditors may need to incorporate digital disclosure credibility into audit planning and risk assessment.

For regulators, the results suggest that digital transformation disclosure requires greater standardization and verifiability. As digital economy policies encourage firms to disclose digital strategies, there is a risk that some firms may use broad or symbolic digital language without providing sufficient supporting evidence. Regulators may consider encouraging firms to provide more comparable and verifiable information about digital transformation, such as digital investment amounts, capitalization policies for digital intangible assets, data resources, IT systems, digital business revenue, and governance mechanisms over digital assets. Such disclosure improvements may reduce information asymmetry and help investors, auditors, and other stakeholders better assess the substance of firms' digital transformation.

5.3. Limitations and Future Research

This study has several limitations. First, *DCI* is an empirical proxy for digital catering. Although it captures the gap between digital narratives and actual digital investment, it does not directly prove that managers intentionally engage in symbolic disclosure or “tech-washing.” Future research may combine textual analysis with regulatory inquiries, management interviews, enforcement cases, or subsequent restatement and misstatement outcomes to better identify intentional digital exaggeration and validate the *DCI* measure, connecting this setting to research on misstatement prediction and machine-learning-based misstatement detection (Bertomeu et al., 2021; Dechow et al., 2011).

Second, actual digital investment is measured using digital-related intangible assets scaled by total intangible assets. This measure captures an important dimension of substantive digital transformation, but it may not fully reflect all digital activities. For example, firms may invest in digital transformation through expenses, outsourced services, cloud computing contracts, employee training, or process redesign that are not fully capitalized

as intangible assets. Future studies may develop broader measures of actual digital transformation using IT staff, digital patents, digital revenue, software expenditures, or data asset disclosures.

Third, although this study uses firm fixed effects, year fixed effects, rich controls, IV tests, and PSM analyses, remaining endogeneity concerns cannot be fully ruled out. The exclusion restriction of the peer digital catering instrument may be challenged if local industry-level digital policies or common regional shocks affect both peer digital catering and focal firms' audit pricing. Therefore, the results should be interpreted as evidence of a robust association rather than definitive causal effects.

Finally, this study focuses on Chinese A-share listed firms. The findings may depend on China's institutional setting, disclosure regulation, audit market structure, and digital economy policies. Future research could examine whether similar audit pricing effects exist in other markets. In addition, China's recent accounting rules on data resources and digital assets may provide useful quasi-natural experimental settings for studying how more standardized digital asset disclosure affects audit pricing, information quality, and capital market outcomes.

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Conflicts of Interest: The author declares no conflicts of interest.

Appendix A

Table A1. Variable definitions.

Variable	Definition	Source
Panel A: Dependent variable		
<i>AuditFee2</i>	Natural logarithm of total audit fees (<i>AuditFee1</i>).	CSMAR
Panel B: Digital catering variables		
<i>DCI</i>	Digital Catering Index = <i>NominalDigitalNorm_{i,t}</i> minus <i>ActualDigitalNorm</i> . Range [−1, 1]. Higher <i>DCI</i> indicates a larger gap between nominal digital disclosure and actual digital investment.	Calculate
<i>NominalDigitalNorm_{i,t}</i>	Industry–year min-max normalized frequency of digital-related keywords per 100 words in the annual report. Range [0, 1]. Raw variable <i>NominalDigital</i> = (digital keyword frequency / total annual report word count) × 100.	Calculate
<i>ActualDigitalNorm</i>	Industry–year min-max normalized share of digital intangible assets in total intangible assets. Range [0, 1]. Raw variable <i>ActualDigital</i> = net digital intangible assets / total intangible assets.	Calculate
<i>DCIZscore</i>	Z-score standardized version of <i>DCI</i> within each industry–year. Used in robustness (Table 5, Col 1).	Calculate

Table A1. Cont.

Variable	Definition	Source
DCIlevel	Difference between the decile rank of <i>NominalDigitalNorm_{i,t}</i> and the decile rank of <i>ActualDigitalNorm</i> within each industry–year. Range [−9, 9]. Used in robustness (Table 5, Col 2).	Calculate
IsDCICatering	Dummy: 1 if <i>NominalDigitalNorm_{i,t}</i> exceeds its industry–year mean and <i>ActualDigitalNorm</i> falls below its industry–year mean. Used in robustness (Table 5, Col 3) and PSM.	Calculate
DCI2Y	Two-year arithmetic mean of <i>DCI</i> (current and prior year). Used in robustness (Table 5, Col 4).	Calculate
DCI3Y	Three-year arithmetic mean of <i>DCI</i> (current and two prior years). Used in robustness (Table 5, Col 5).	Calculate
Panel C: Control variables—Financial characteristics		
Size	Natural logarithm of total assets.	CSMAR
Lev	Total liabilities/Total assets.	CSMAR
ROA	Net income/Average total assets.	CSMAR
Growth	Revenue growth rate: (current revenue − prior revenue)/ prior revenue .	CSMAR
CashFlow	Net operating cash flow/Total assets.	CSMAR
BM	Book value of equity/Market value of equity.	CSMAR
FirmAge	ln(1 + years since firm establishment).	CSMAR
Rec	Accounts receivable/Total assets.	CSMAR
Inv	Inventory/Total assets.	CSMAR
Intangible	Intangible assets/Total assets.	CSMAR
Panel D: Control variables—Corporate governance		
Board	ln (number of board directors).	CSMAR
Indep	Independent directors/Total board directors.	CSMAR
Top1	Shareholding percentage of the largest shareholder.	CSMAR
Dual	Dummy: 1 if CEO also serves as board chair.	CSMAR
Inst	Shareholding percentage of institutional investors.	CSMAR
SOE	Dummy: 1 if ultimately controlled by the government.	CSMAR
Panel E: Control variables—Auditor characteristics		
IsBig4	Dummy: 1 if audited by a Big 4 firm (PwC, Deloitte, EY, KPMG).	Calculate
AuditorTenure	Number of consecutive years the current audit firm has been engaged.	Calculate
AuditorChange	Dummy: 1 if the firm changed its audit firm in the current year.	Calculate
NonStandardOpinion	Dummy: 1 if the audit opinion is not a standard unqualified opinion (=1 − Opinion). Opinion is from CSMAR.	Calculate

Table A1. Cont.

Variable	Definition	Source
Panel F: Control variables—Text characteristics and business complexity		
lnDocTokenCount	$\ln(1 + \text{DocTokenCount})$. DocTokenCount is the number of Chinese-character words retained after tokenization and frequency filtering for LDA topic modeling of the annual report.	Calculate
lnFileLen	$\ln(1 + \text{FileLen})$. FileLen is the total character count of the annual report. Replaces lnDocTokenCount in robustness (Table 7, Col 4).	Calculate
MDAReadabilityPCA	PCA first principal component of four sub-indicators (MDAAvgSentLen, MDARareCharRatio, MDANumCharRatio, MDAProfTermRatio) computed from the MD&A section. Higher values indicate lower readability. Also used as a channel variable (Table 9, Col 1).	Calculate
Similarity	Cosine similarity between the firm's annual report LDA topic distribution vector (100 topics) and the industry-year average topic vector. Range [0, 1]. Higher values indicate more boilerplate disclosure. Also used as a channel variable (Table 9, Col 2). Note: mechanically correlated with lnDocTokenCount and NumPeers.	Calculate
BusinessComplexity	Number of CSRC industry categories spanned by the firm's principal operating revenue segments. Manufacturing industries retain one-digit codes (C1–C9); other sectors use letter codes. Larger values indicate greater business complexity.	Calculate
Panel G: Mechanism-related variables		
MDAReadabilityPCA	See Panel F. Mechanism-related outcome: information opacity. Higher <i>DCI</i> → lower MD&A readability.	Calculate
Similarity	See Panel F. Mechanism-related outcome: boilerplate disclosure. Higher <i>DCI</i> → more templated annual reports. Regression additionally controls for lnDocTokenCount and NumPeers due to mechanical correlation (see Similarity data documentation).	Calculate
lnDelay	$\ln(\text{ReportingLag} + 1)$, where ReportingLag = days between fiscal year-end (Accper) and actual disclosure date (Actudt). Mechanism-related outcome: audit/reporting complexity. Higher <i>DCI</i> → longer reporting lag.	CSMAR
NCSKEW_Mdeq (t + 1)	Negative conditional return skewness, market-cap equal-weighted, led by one year. Mechanism-related outcome: future stock price crash risk. Higher <i>DCI</i> → higher future crash risk.	CSMAR
DUVOL_Mdeq (t + 1)	Down-to-up volatility ratio, market-cap equal-weighted, led by one year. Alternative crash risk measure.	CSMAR
Panel H: Cross-sectional heterogeneity variables		
SOE	See Panel D. Interacted with <i>DCI</i> (Table 10, Col 1). Prediction: SOEs benefit from implicit government guarantees → weaker <i>DCI</i> –audit fee association.	CSMAR
PriorLoss	Dummy: 1 if the firm reported a net loss in the prior year. Interacted with <i>DCI</i> (Table 10, Col 2). Prediction: loss firms face stronger earnings pressure → stronger association.	CSMAR

Table A1. Cont.

Variable	Definition	Source
HighInst	Dummy: 1 if institutional ownership (Inst) exceeds the annual median. Interacted with <i>DCI</i> (Table 10, Col 3). Prediction: strong external monitoring → weaker association.	CSMAR
LowActualDigital	Dummy: 1 if <i>ActualDigitalNorm</i> is below its industry–year median. Interacted with <i>NominalDigitalNorm_{i,t}</i> (Table 6, Col 5). Prediction: nominal digital disclosure premium concentrated in firms with low actual digital investment.	Constructed
Panel I: Instrumental variable		
PeerDCI	Leave-one-out mean <i>DCI</i> of all other firms in the same industry–province–year group. $PeerDCI_{i,t} = \text{mean}(DCI_{j,t})$ for j in the same group, $j \neq i$. Groups require at least 5 firms.	Constructed from <i>DCI</i>
Panel J: Other variables used in variable construction		
Opinion	Dummy: 1 for standard unqualified audit opinion. Used to construct $NonStandardOpinion = 1 - Opinion$.	CSMAR
Actudt	Actual annual report disclosure date (YYYY-MM-DD). Used to construct $ReportingLag = Actudt - Accper$.	CSMAR
Accper	Fiscal year-end date (YYYY-MM-DD).	CSMAR
DocTokenCount	Word count of the annual report after Chinese tokenization, retaining only Chinese-character words and applying frequency filtering (appearing in ≥ 20 and $\leq 50\%$ of reports, $vocab \leq 10,000$). Used as denominator for LDA topic modeling and to construct $LnDocTokenCount$.	Calculate
NumPeers	Number of comparable peer firms in the same CSRC industry–year group (manufacturing: 2-digit code; non-manufacturing: letter code), excluding the focal firm. Controlled in the Similarity channel regression.	Calculate
Industry3/ProvinceCode	CSRC industry classification (sector level) and province administrative code. Used for fixed effects, IV peer group construction, and PSM.	CSMAR

Notes: All continuous variables are winsorized at the 1st and 99th percentiles. CSMAR = China Stock Market and Accounting Research Database. The baseline sample consists of 31,753 firm-year observations from 4879 Chinese A-share listed firms over 2015–2024. Industry classification follows the CSRC standard: manufacturing firms use two-digit codes; non-manufacturing firms use sector-level letter codes. All regressions include firm and year fixed effects with standard errors clustered at the firm level.

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