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Does Readability of Digital Transformation Information Disclosure Affect Asset Mispricing? A Signaling Theory Perspective

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Abstract

This study examines the impact of the readability of corporate digital transformation disclosures on asset mispricing. Digital transformation for enterprises represents a profound process of organizational change, significantly affecting internal value enhancement and external stakeholders. However, the issue of information asymmetry during the digital transformation process attracts great attention. Based on signaling theory, this paper constructs a readability index for corporate disclosures on digital transformation through text analysis and empirically examines its subsequent impact on asset mispricing. Our findings suggest that highly readable disclosure on digital transformation reduces information asymmetry, thereby alleviating asset mispricing significantly, with media attention and technological intensity playing roles of moderators in the signaling environment. This research provides theoretical support and practical guidance for corporate digital transformation and disclosure strategies, contributing to investor decision-making and fostering the healthy development of capital markets.

Keywords

Digital Transformation, Signaling Theory, Readability, Asset Mispricing

1. Introduction

Digital transformation leads to a comprehensive and profound change for enterprises, which optimizes and reengineers business processes through the digital technology adoption process (Vial, 2021). This transformation not only serves as a critical factor in driving organizational development and enhancing competitiveness (Zhang et al., 2023; Chen et al., 2020; Liu et al., 2020), but also deeply influences the operational modes and investment strategies of the capital market (Yu et al., 2023b; Wu et al., 2021). However, digital transformation often involves high financial cost and time cost, and its returns are uncertain (Karimi & Walter, 2016; Müller et al., 2018). Such ambiguity reduces investor confidence (Cai et al., 2022) and diminishes capital gains (Xu & Xu, 2015), which leads stakeholders confused about the accurate asset value brought by digital transformation.

Former research on the theme of digital transformation focuses on elucidating key success factors of the transformation process (Vogelsang et al., 2018), its evolutionary paths (Berman, 2012), and mechanisms behind it (Jiao et al., 2021). However, the gauge of the value of on-going digital transformation is unwarranted, which leaves uncertainty and potential risk until years after the digital transformation projects are implemented (Gökalp & Martinez, 2021). Therefore, our research focuses on the following research questions: 1) How to uncover the uncertain and ambiguous digital transformation information during its process? 2) Does this extra disclosed information of on-going digital transformation alleviate enterprises' current asset mispricing? And how?

To achieve a more profound understanding of the digital transformation process, the application of text analysis to the annual reports of publicly traded companies presents a feasible solution. Compared to structured financial statement data, text mining based on annual report information captures non-financial insights such as management sentiment, management style, and decision-making intentions (Gentzkow et al., 2019). Such analysis tool enhances the precision of earnings forecasts (Loughran & McDonald, 2014) and supports the interpretation of capital market valuation (Caglio et al., 2020).

Our study contributes to the current literature in the following ways. First, given the context of disclosed digital transformational information from annual reports, our research provides a quantitative method of gauging the asset value generated digital transformation process by the textual analysis. Secondly, we investigate how digital transformation information index, name readability of digital transformation information disclosure hereinafter, could lead to lower asset mispricing. The signal theory is adopted and a theoretical explanation is illustrated and tested under an empirical study.

The rest of this paper proceeds as follows. Section 2 reviews literature of digital transformation. Section 3 proposes the research hypotheses. The methodology is described in Section 4, and data analysis results are reported in Section 5. Finally, Section 6 discusses the contributions of this study and directions for future research.

2. Literature Review

2.1. Digital Transformation and Its Value

Digital transformation has been defined as a key process for enterprises to implement deep, systematic, and comprehensive changes, with the core being to reshape and optimize their business activities through the deep integration of digital technology (Vial, 2021). This transformation not only significantly improves internal operational efficiency (Yu et al., 2022) and innovates business models (Chen et al., 2020), but also promotes the optimization of organizational structure (Liu et al., 2020; Yuan et al., 2021), thereby better adapting to market demand. This transformation not only has a profound impact on the internal structure of enterprises, but also involves external stakeholders such as increasing government subsidies (Yu et al., 2023a), influencing supply chain behavior (Du et al., 2023), shaping organizational reputation (Salge et al., 2022), and enhancing capital market feedback (Wu et al., 2021).

However, digital transformation is not an easy task. The process is not only time-consuming, labor-intensive and tame-taking, the relative returns are uncertain as well (Karimi & Walter, 2016; Müller et al., 2018). In the early stages of transformation, enterprises often face the dilemma of increased investment in accompanying unobserved improved efficiency, Liu et al. (2020) find an inverted "U" shape relationship between investment and efficiency, which shows there is no necessary connection between the them (Liu et al., 2020). At the same time, the integration of digital technology and existing resources of enterprises may also lead to an increase in management costs, which undoubtedly increases the economic pressure and complexity of transformation (Qi & Xiao, 2020). The challenges and uncertainties brought about by digital transformation have exacerbated the problem of information asymmetry between enterprises and investors, which may have a negative impact on investor confidence and market evaluation of enterprises (Cai et al., 2022; Xu & Xu, 2015).

Previous studies have found that digital transformation information disclosure can reduce information asymmetry and have a positive impact on the capital market (Yu et al., 2023b; Sun & Shi, 2023), especially in highly competitive or technology intensive fields (Sha & Xu, 2024). However, information disclosure may also introduce negative information, that is, due to the long-term and high investment feature of transformation, relevant information may be manipulated, leading to conceptual hype and performance decline (Ma et al., 2023; Cao et al., 2023). Therefore, there exist gaps about how to capture the process of digital transformation limited by structural data.

2.2. Text Readability of Information Disclosure

The textual features of corporate information disclosure provide rich information for capital market research (Li, 2008; Wang et al., 2018a). Among them, readability is a key indicator that directly affects the efficiency and accuracy of information reception (Sawyer et al., 2008). Improved text readability helps to reduce information noise and attract investors (Burtch et al., 2013; Chen et al., 2018b). Based on the theory of vague management, enterprise management may mask negative impacts by means of reducing the readability of annual reports (Li, 2008). For example, pledging equity of controlling shareholders can also lead to a decrease in the readability of annual reports (Lu et al., 2020), and management tends to use complex vocabulary to blur the true situation when performance is poor (Wang et al., 2018a), which increases the difficulty for investors to interpret the true situation of the company.

In the financial field, there are many methods for gauging readability, among which the Gunning Fog Index measures the readability of a text by the proportion of complex vocabulary and average word length, and has been applied in the study of annual report readability and investment decision-making (Li, 2008; Lawrence, 2013). In order to better fit the Chinese context, some studies provide improved methods, such as using indicators such as Chinese character strokes, basic vocabulary ratio, and percentage of complete sentences (Qiu et al., 2016), measuring annual report information using commonly used Chinese characters and word ratios (Meng et al., 2017), and using indicators such as accounting terminology density (Wang et al., 2018a). At present, these methods are mainly used to interpret sustainable development reports (Smeuninx et al., 2020), social responsibility reports (Du & Yu, 2021), insurance clauses (Van Boom et al., 2016), online health platform information (Mcinnes & Haglund, 2011), and fundraising texts (Kamatham et al., 2021). However, there are currently no precedents for in-depth research on the readability characteristics of texts related to digital transformation. Therefore, there exist a gap of how to gauge text readability suitable for digital transformational context and how this readability index provides extra information for stakeholders is unwarranted.

2.3. Information Disclosure and Asset Mispricing

Asset mispricing refers to the phenomenon that the market value of a listed company deviates from its intrinsic value due to factors such as information asymmetry and cognitive biases among market participants (Chaney & Lewis, 1995). Asymmetric information makes it difficult for investors to assess accurate value and to make correct investment decisions, while these cognitive biases among investors further result in biased estimates of asset values. Former research found that the causes of asset mispricing include: 1) In terms of disclosure and transmission: corporate annual reports (Xu & Xu, 2015), conference call records (Chen et al., 2018a), and media coverage content (Huang & Guo, 2014), etc; 2) In terms of disclosure content, information disclosure on green environmental protection (Caglio et al., 2020;) and social responsibility (Dhaliwal et al., 2011; Chen et al., 2022) can effectively alleviate information asymmetry.

The measure of asset mispricing is based on stock price performance (Morck et al., 2000) or the difference between the actual value of a company and its industry base value (Berger & Ofek, 1995; Doukas et al., 2010). Xu and Xu (2015) used the ratio of intrinsic value to market value (V/P) as an indicator to measure the degree of inconsistency between the market value and intrinsic value of listed companies. The intrinsic value per share (V) of a listed company is estimated using the residual income model (RIM) (Feltham & Ohlson, 1995), while P represents the annual average closing price of the company's stock. Digital transformation, as an important trend in the current development of enterprises, deserves further exploration in the relationship between digital transformation disclosure and asset mispricing.

2.4. Signaling Theory and Information Disclosure as Signal Transmission

Signal transmission refers to the process in which a signal is sent by the signal sender to the signal receiver, while the whole process is evaluated and decided upon under the influence of environmental factors (Connelly et al., 2011). The sender of the signal, as an insider (such as a corporate executive), possesses core company information that is of significant value to external decision-makers (Connelly et al., 2011). In the process of signal transmission, signal effectiveness is influenced by various factors, including transmission cost, observability, signal strength, and receiver characteristics (such as environmental sensitivity and signal capture ability) (Bergh et al., 2014; Branzei et al., 2004). In the process of market trading, the information dominant party gains an advantage by possessing information or receiving signals (Akerlof, 1970), and the complex and diverse signal environment can also lead to signal effectiveness variously among different environment (Lester et al., 2006).

The signaling theory provides a theoretical framework for market information transmission, and information advantages can reduce information asymmetry through information disclosure (Spence, 1978), and enhance information transparency and trust (Moker et al., 2020). Enterprises can disclose information to stakeholders through regular structured reports, conference calls (Davis et al., 2015; Chen et al., 2018a), news reports (Ostrovsky-Berman, 2021), and corporate social responsibility reports (Wang et al., 2014). Especially, the "Management Discussion and Analysis" section of the company's annual report, which displays the management's views on the company's performance and future development, has a profound impact on investor decision-making (Meng et al., 2017; Wang et al., 2018b).

In summary, we believe that disclosed digital transformation texts serve as a signal for companies to enhance market transparency and reduce asset mispricing. However, existing research focuses more on the frequency of disclosure, therefore there lacks in-depth exploration of textual features such as the text readability. In our research, we will delve deeper into the readability of digital transformation information disclosure, and comprehensively evaluate the impact of signal transmission on asset mispricing from the perspectives of signal senders, signal receivers, and signal environments.

3. Theoretical Hypothesis

3.1. Readability of Information Disclosure in Digital Transformation and Asset Mispricing

Digital transformation is a complex and continuous process. On the one hand, low readability texts may indicate a higher tendency for information manipulation. Due to a significant information gap between companies and investors, the disclosed texts with low readability increases the difficulty of external supervision (Gosselin et al., 2021), which reduces information transparency and thus increases the risk of capital mispricing. On the other hand, highly readable texts effectively reduce information noise, making signal receivers less susceptible to being misled by information manipulation. When a company uses clear and understandable text for information disclosure, its investors can quickly and accurately grasp the essence of the company's disclosure, which leads to wiser investment decisions (Burtch et al., 2013; Chen et al., 2018b).

Therefore, this article believes that the readability of digital transformation information disclosure in annual reports serves as an important signal to increase the transparency of enterprise digital transformation, reduce information asymmetry, and reduce the degree of deviation of market value of listed companies from their intrinsic value. In summary, this article proposes the following assumptions:

H1: The readability of disclosed enterprise digital transformation information alleviates asset mispricing, that is, there is a negative correlation between the readability of enterprise digital transformation information disclosure and asset mispricing.

3.2. Media Environment: The Moderating Effect of Media Attention

The signaling theory explicitly highlights the crucial role of the signal environment in the transmission, reception, and interpretation of signals. The level of media attention significantly impacts the effectiveness of signal transmission.

Firstly, the increase in high media attention directly broadens the channels for obtaining signals, while the increased the number of observable signals further enhances signal efficiency (Lester et al., 2006). As more and more media cover one company, market participants can more conveniently obtain information about the company (Peress, 2014). For example, information on a company's digital transformation achievements, strategic planning or implementation progress in the forms of text, images or videos might be presented to market participants through various kinds of media platforms, which greatly enhances the accessibility and comprehensibility of the information.

Secondly, a high level of media attention also attracts the interest of market participants. Information intermediaries such as analysts and auditors, upon receiving media coverage, are further motivated to conduct in-depth analysis and investigation of the company's information (Miller, 2006). They provide investors with more detailed and in-depth analysis reports by conducting in-depth research on various aspects of corporate digital transformation, including technology investment, business model innovation, market response, etc. This not only helps investors in gaining a more holistic understanding of corporate digital transformation but also enhances the transparency and accuracy of information, thereby offering a more robust foundation for investment decisions.

The increase in media attention heightens the focus of investors and other market participants on signals related to corporate digital transformation, thereby further reducing information asymmetry. This reduction in information asymmetry aids investors in more accurately assessing the value of the company. Therefore, this paper proposes the following hypothesis:

H2: When a company receives high media attention, the negative relationship between the readability of its digital transformation information disclosure and its asset mispricing is strengthened.

3.3. Technical Environment: The Regulatory Role of Technology Intensity

During the process of enterprise digital transformation, the signal transmission efficiency of the disclosed information readability is also influenced by the industry environment. Specifically, the unique nature of technology intensive enterprises may become the main obstacle to signal transmission.

Firstly, the operating environment of technology intensive enterprises is full of uncertainty. Due to rapid technological updates and fierce market competition, when enterprises carry out value investment, the investment direction is broader and the investment effect deviation is greater (Liao et al., 2015). In the technology-intensive industry environment, it is difficult to accurately predict the future technological development trends and potential market changes. Therefore, even if the disclosed information readability is high, investors may still make investment decisions that deviate from the actual value of the enterprise.

Secondly, technology intensive enterprises may maintain a certain degree of caution and confidentiality in information disclosure in order to protect their core technologies and trade secrets (Bar-Gill & Parchomovsky, 2009). This confidentiality may lead to a decrease in signal observability, thereby limiting the effectiveness of improving the readability of digital transformation information in reducing information asymmetry.

In addition, the products and services of technology intensive enterprises often involve complex assets such as intellectual property, scientific research achievements, and patented technologies. These assets have high cognitive barriers for nonprofessional investors, which increases the difficulty for investors to understand the operational status and future development prospects of the enterprise (Borello et al., 2019).

Based on the above analysis, the environmental characteristics of technology intensive enterprises limit the effectiveness of their digital information disclosure readability as the diagnosis in reducing information asymmetry. Correspondingly, this limitation also weakens the corrective effect of readability signals on asset pricing bias. Therefore, this article proposes the following assumptions:

H3: When a company has a high level of technological intensity, the negative relationship between the readability of digital transformation information disclosure and asset mispricing will be weakened.

4. Research Methodology

4.1. Sample Selection

This study focuses on A-share non-financial listed companies on the Shanghai and Shenzhen stock exchanges from 2010 to 2021 in China. The data was sourced from annual reports of listed companies, the CSMAR database, and the CEDS database. After excluding ST stocks, delisted companies, companies listed for less than a year, and financial industry samples, a total of 16,484 observations from 3288 companies were obtained for this study. To process the data, the explanatory variables were set to lag one period, and the extreme values (top 1% and bottom 1%) of the continuous variables were winsorized.

4.2. Variable Measurement

1) Dependent Variable: Asset Mispricing (|Deviation|)

Asset mispricing refers to the discrepancy between the market value of a listed company and its intrinsic value. This calculation utilizes the V/P ratio (intrinsic value to market value) as a key reference indicator. The intrinsic value per share (V) of a listed company is estimated using the residual income model (RIM), while P represents the annual average closing stock price. A V/P ratio of 1 indicates that the market value accurately reflects intrinsic value. If the V/P ratio is less than 1, the market overvalues the company's intrinsic value, with a lower ratio indicating a higher degree of overvaluation. Conversely, when the V/P ratio exceeds 1, the market undervalues the company's intrinsic value. This study refers to Xu and Xu (2015) using Formula (1) variable to quantify the absolute value of the degree of deviation. The magnitude of this deviation correlates positively with the value, indicating a higher degree of asset mispricing with a larger value.

$$\left|\text{Deviation}\right| = \left|1 - \text{V/P}\right| . \tag{1}$$

2) Independent Variable: Readability of Digital Transformation Information Disclosure (Readability)

This study refers to the digital key word library constructed by Wu et al. (2021) and extracts sentences containing these keywords from the annual report "Management Discussion and Analysis" as analytical text. According to the readability measurement proposed by Meng et al. (2017), the calculation of the proportion of vocabulary in the text that complies with the General and Standard Chinese Characters Table (State Language Commission, 2013) is shown in Formula (2). A high proportion means strong readability.

$$\text{Readability}_{i,t} = \text{N\_common}_{i,t} / \text{N\_sentence}_{i,t} \quad (2)$$

where $\text{N\_common}_{i,t}$ is the number of common terms included in the digital text of company i in the t annual report, and $\text{N\_sentence}_{i,t}$ is the total number of terms in the digital text of company i in the t annual report.

3) Moderating Variables: Media Attention (Media_Att), Technology Intensity (High_Tech)

This study uses the logarithm of the total number of reports on specific enterprises in online news content throughout the year as an indicator to measure the level of media attention of enterprises (Yu et al., 2023b). This study strictly followed the industry classification standards of the Classification of High-Tech Industries (Manufacturing Industry) (National Bureau of Statistics, 2013a) and the Classification of High-Tech Industries (Service Industry) (National Bureau of Statistics, 2013b) issued by the National Bureau of Statistics of China, and determined the industry codes for high-tech intensive listed companies required for the study (Bai, 2022). If the enterprise is a high-tech intensive industry, the value is 1, otherwise it is 0.

4) Control variables

This study considers both the size of the enterprise and the age of its listing, while also takes into account of the financial condition and internal governance structure. We assess profitability using the net profit margin of total assets and growth potential using Tobin's Q value. In terms of governance, we have controlled for the nature of equity, the integration of dual roles, and the concentration of equity. Additionally, the readability of the annual report was considered to prevent its interference with the results. Detailed definitions and measurement methods for all variables are summarized in **Table 1**.

4.3. Model Design

This chapter employs panel data regression analysis to validate the theoretical model and hypotheses. Initially, the Hausman test is conducted to determine the appropriate estimation technique. Based on the test results, we proceed with a high-dimensional panel fixed effects estimation method. To ensure robustness, we apply clustering at the company level to correct standard errors. The benchmark regression model for this chapter is detailed in Equation (3), which is used to analyze the impact of digital transformation readability on asset mispricing.

$$\left|\text{Deviation}\right|_{i,t+1} = \beta_0 + \beta_1 \text{Readability}_{i,t} + \sum\nolimits_{j=1}^{n} \theta_j \text{CV}_{i,t} + \mu_{i,\text{year}} + \nu_{i,\text{industry}} + \varepsilon_{i,t} \quad (3)$$

$$\begin{aligned} \left|\text{Deviation}\right|_{i,t+1} = {} & \beta_0 + \beta_1 \text{Readability}_{i,t} + \beta_2 \text{Readability}_{i,t} \times \text{Media\_Att}_{i,t} \\ & + \beta_3 \text{Media\_Focus}_{i,t} + \sum\nolimits_{j=1}^{n} \theta_j \text{CV}_{i,t} + \mu_{i,\text{year}} + \nu_{i,\text{industry}} + \varepsilon_{i,t} \end{aligned} \quad (4)$$

$$\begin{aligned} \left|\text{Deviation}\right|_{i,t+1} = {} & \beta_0 + \beta_1 \text{Readability}_{i,t} + \beta_2 \text{Readability}_{i,t} \times \text{High\_Tech}_{i,t} \\ & + \beta_3 \text{High\_Tech}_{i,t} + \sum\nolimits_{j=1}^{n} \theta_j \text{CV}_{i,t} + \mu_{i,\text{year}} + \nu_{i,\text{industry}} + \varepsilon_{i,t} \end{aligned} \quad (5)$$

Table 1. Detailed definitions and measurement methods of variables.

Variable Category	Variable Name	Symbol	Measurement Method	Data Source
Dependent Variable	Asset Mispricing	|Deviation|	Absolute value of 1 minus the ratio of intrinsic value to market value (V/P), as shown in Formula (1) (Xu & Xu, 2015)	CSMAR
Independent Variable	Readability of digital transformation information disclosure	Readability	According to the readability measurement method proposed by Meng et al. (2017), calculate the proportion of vocabulary in the text that complies with the General and Standard Chinese Characters Table (State Language Commission, 2013), as shown in Formula (2)	Annual reports of listed companies
Moderating Variables	Media Attention	Media_Att	Natural logarithm of the total number of news headlines mentioning the company throughout the year (plus 1) (Yu et al., 2023b)	CEDS
	High-Tech Industry Affiliation, i.e. Technology Intensity	High_Tech	Value is 1 if the enterprise belongs to the high-tech industry according to "the Classification of High-Tech Industries (Manufacturing Industry) (National Bureau of Statistics, 2013a)" and "the Classification of High-Tech Industries (Service Industry) (National Bureau of Statistics, 2013b)" in China; otherwise, the value is 0 (Bai, 2022)	See 4.2 for details
Control Variables	Company Size	Ln_Size	Natural logarithm of total annual assets	CSMAR
	Years Listed	FAge	Ln (current year − listing year + 1)	CSMAR
	Return on Total Assets	ROA	Net profit/Average total assets	CSMAR
	Tobin's Q	TobinQ	(Market value of tradable shares + Non-tradable shares × Net asset value per share + Book value of liabilities)/Total assets	CSMAR
	Duality of Roles	Dual	1 if the chairman and general manager are the same person; otherwise, 0	CSMAR
	Largest Shareholder's Stake	Top1	Number of shares held by the largest shareholder/Total number of shares	CSMAR
	State-Owned Enterprise	SOE	1 for state-owned holding enterprises, 0 for others	CSMAR
	Annual Report Readability	All_ Readability	Refer to the "Readability" calculation method to calculate the readability of the "Management Discussion and Analysis" section in the annual report.	Annual reports of listed companies

$$\begin{aligned}\left|\text{Deviation}\right|_{i,t+1} = {} & \beta_0 + \beta_1 \text{Readability}_{i,t} + \beta_2 \text{Readability}_{i,t} \times \text{Media\_Focus}_{i,t} \\ & + \beta_3 \text{Media\_Att}_{i,t} + \beta_4 \text{Readability}_{i,t} \times \text{High\_Tech}_{i,t} \\ & + \beta_5 \text{High\_Tech}_{i,t} + \sum_{j=1}^{n} \theta_j \text{CV}_{i,t} + \mu_{i,\text{year}} + \nu_{i,\text{industry}} + \varepsilon_{i,t}\end{aligned} \tag{6}$$

This study takes asset mispricing (|Deviation|) as the dependent variable and readability of disclosed digital transformation information as the explanatory variable. To avoid endogeneity issues, all explanatory variables are lagged by one period. The model also includes control variables (CV), as well as year and industry fixed effects ($\mu_{i,\text{year}}$, $\nu_{i,\text{industry}}$).

In Equations (4) and (5), moderating variables of media attention (Media_Att) and technological intensity (High_Tech), along with their interaction terms, are added respectively. Equation (6) simultaneously incorporates both moderating variables and their interaction terms.

5. Empirical Results Analysis

5.1. Descriptive Statistics

Table 2 presents the descriptive statistical results of the key variables in this chapter. By observing the table, it can be seen that the mean of asset mispricing (|Deviation|) is 0.668, with a variance of 0.477.

5.2. Correlation Analysis and Multicollinearity Test

Table 3 presents the correlation analysis of the main variables in this chapter. The VIF values in this paper are all less than 2, with an average VIF value of 1.320, indicating that there is no significant multicollinearity among the variables in the regression model (Farrar & Glauber, 1967).

5.3. Regression Analysis

Table 4 presents the analysis results of various panel fixed effects models in this

Table 2. Descriptive statistics.

Variable Type	Variable	N	Mean	SD	Min	Max
DV	|Deviation|	16,484	0.668	0.477	0.016	2.930
IV	Readability	16,484	0.264	0.252	0	1
MV	Media_Att	16,484	5.065	1.045	0.693	10.808
	High_Tech	16,484	0.491	0.500	0	1
CV	ROA	16,484	0.033	0.079	−2.646	0.786
	TobinQ	16,484	2.062	1.420	0.802	15.607
	Ln_Size	16,484	22.452	1.311	14.942	28.637
	List_Age	16,484	2.329	0.658	1.099	3.367
	SOE	16,484	0.403	0.490	0	1
	Dual	16,484	0.253	0.435	0	1
	Top1	16,484	34.208	14.616	8.087	75.779
	All_Tone	16,484	−0.007	0.0658	−0.457	0.509
	All_Readability	16,484	−24.268	5.102	−132.174	−8.090

Table 3. Correlation analysis.

	Variable	1	2	3	4	5	6	
1	|Deviation|	1						
2	Readability	0.012*	1					
3	Media_Att	0.072***	0.012*	1				
4	High_Tech	−0.028***	0.159***	−0.084***	1			
5	ROA	−0.378***	0.022***	0.079***	0.023***	1		
6	SOE	0.024***	−0.115***	0.084***	−0.193***	−0.039***	1	
7	Dual	−0.00200	0.089***	−0.037***	0.121***	0.00900	−0.298***	
8	Ln_Size	0.067***	0.033***	0.412***	−0.233***	0.056***	0.330***	
9	List_Age	0.071***	−0.048***	0.067***	−0.233***	−0.104***	0.456***	
10	Top1	−0.043***	−0.051***	0.089***	−0.153***	0.122***	0.234***	
11	TobinQ	0.072***	0.062***	0.092***	0.174***	0.115***	−0.168***	
12	All_Readability	0.0110	−0.198***	−0.019***	−0.123***	−0.024***	0.110***	
13	All_Tone	−0.080***	0.089***	0.048***	0.198***	0.179***	−0.221***	
		7	8	9	10	11	12	13
7	Dual	1						
8	Ln_Size	−0.157***	1					
9	List_Age	−0.235***	0.352***	1				
10	Top1	−0.064***	0.227***	−0.033***	1			
11	TobinQ	0.085***	−0.405***	−0.087***	−0.104***	1		
12	All_Readability	−0.063***	−0.039***	0.088***	0.041***	0.00800	1	
13	All_Tone	0.104***	−0.149***	−0.344***	−0.050***	0.082***	−0.303***	1

Note: ***, **, and * indicate that the coefficient is significant at the 1%, 5%, and 10% levels.

study in detail, including the main effect model and the interaction effect model.

1) Main Effect Test

Model (1) presents the regression results that only include explanatory and control variables. Table 4 shows that the readability of digital transformation information disclosure (Readability) has a significant negative impact on asset mispricing (|Deviation|). This result verifies H1 of this sub-study, which states that the readability of a company's digital transformation information disclosure can effectively improve its pricing efficiency in asset value and alleviate asset mispricing.

2) Moderating Effect Test

Models (2) and (3) report the results of moderating effects. As shown in the Table 4, in Model (2), the interaction term between media attention and the readability of digital transformation information disclosure (Media_Att × Readability) is significantly negative, aligning with the main effect sign. The level of

Table 4. Results of panel fixed effects model.

Variable	Model (1) |Deviation|	Model (2) |Deviation|	Model (3) |Deviation|	Model (4) |Deviation|
Readability (H1)	**−0.056*** **	**−0.059*** **	**−0.050*** **	**−0.053*** **
	(−2.972)	**(−3.117)**	**(−2.733)**	**(−2.921)**
Media_Att × Readability (H2)		**−0.067*** **		**−0.064*** **
		(−3.525)		**(−3.400)**
Media_Att		**0.017** **		**0.017** **
		(2.441)		**(2.400)**
High_Tech × Readability (H3)			**0.097*** **	**0.084** **
			(2.827)	**(2.479)**
High_Tech			**0.009**	**0.010**
			(0.544)	**(0.607)**
ROA	−0.898***	−0.894***	−0.901***	−0.896***
	(−10.530)	(−10.439)	(−10.599)	(−10.495)
SOE	−0.003	−0.002	−0.003	−0.002
	(−0.231)	(−0.142)	(−0.236)	(−0.149)
Dual	0.011	0.010	0.011	0.010
	(1.060)	(0.993)	(1.067)	(0.999)
Ln_Size	0.035***	0.027***	0.035***	0.028***
	(3.861)	(2.726)	(3.900)	(2.755)
List_Age	0.002	0.004	0.002	0.004
	(0.173)	(0.328)	(0.119)	(0.283)
Top1	−0.001***	−0.001***	−0.001***	−0.001***
	(−2.689)	(−2.606)	(−2.710)	(−2.623)
TobinQ	0.038***	0.036***	0.038***	0.036***
	(10.869)	(9.301)	(10.849)	(9.243)
All_Readability	0.000	0.000	0.000	0.000
	(0.187)	(0.192)	(0.299)	(0.296)
All_Tone	−0.149	−0.142	−0.149	−0.143
	(−1.421)	(−1.357)	(−1.415)	(−1.359)
Year	controlled	controlled	controlled	controlled
Industry	controlled	controlled	controlled	controlled
Constant Terms	−0.140	−0.054	−0.151	−0.065
	(−0.724)	(−0.268)	(−0.787)	(−0.324)
N	16484	16484	16484	16484
adj. R^2	0.085	0.087	0.085	0.087

Note: ***, **, and * indicate that the coefficient is significant at the 1%, 5%, and 10% levels, respectively; the t-value is enclosed in parentheses.

media attention reinforces the negative correlation between the readability of digital transformation information disclosure and asset mispricing. Therefore, H2 is supported. In Model (3), the interaction between technological intensity and the readability of digital transformation information disclosure (High_Tech × Readability) is significantly positive. This validates H3, which proposes that a company's technological intensity weakens the negative correlation between the readability of digital transformation information disclosure and asset mispricing. Model (4) incorporates both moderating effects, and H2 and H3 are supported.

5.4. Robustness Test

1) Changing the Measurement of Independent Variable: The Readability of Digital Transformation Information Disclosure

Annual reports extensively use professional terms such as "profit and loss" and "impairment", which reduces text readability (Wang et al., 2018a). To test robustness, we refer to Wang et al. (2018a) and replace the original independent variable, with the inverse of the number of accounting terminology per 100 words. The regression results after replacement are consistent with the original results (see **Table A1** for details), verifying hypotheses H1, H2, and H3 in this chapter.

2) Changing the Measurement of Moderating Variables: Media Attention (Media_Att) and Technology Intensity (High_Tech)

To further verify robustness, we replace the moderating variables. The new media attention uses the number of online and newspaper news reports throughout the year as an indicator (logarithmic processing), and technology intensity adopts the definition method of Kai and Ya (2020). The regression results after replacement are consistent with the previous results (see **Table A2** for details), once again confirming the correctness of hypotheses H1, H2, and H3.

6. Research Conclusion and Prospects

6.1. Research Conclusion

1) Theoretical Aspects

Firstly, this paper defines the measurement indicator for the quality of digital transformation information disclosure, "readability of digital transformation information disclosure", and provides a quantitative measurement method. Secondly, based on signal theory, a theoretical model is constructed to propose the mechanism and boundary conditions for alleviating asset mispricing by disclosing information readability in digital transformation. Empirical tests show a significant negative correlation between the readability of digital transformation information disclosure and asset mispricing. Media attention and technological intensity can enhance and weaken this negative correlation, respectively.

2) Practical Implications

This study provides theoretical and empirical support for assessing a company's digitization process and quantifying the asset value of digital transformation. Through text analysis techniques, this study also offers a new perspective and insight into the decision-making usefulness of unstructured information in the "Management Discussion and Analysis" section of annual reports.

6.2. Research Prospects

While this study has yielded significant insights, there are inherent limitations that necessitate further exploration. Future investigations should strive to broaden the data scope and refine the construction of asset valuation anomaly indicators.

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Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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Appendix

Table A1. Panel fixed effects model results after changing the independent variable measure.

Variable	(1) |Deviation|	(2) |Deviation|	(3) |Deviation|	(4) |Deviation|
Readability (H1)	**−0.001****	**−0.001****	**−0.001***	**−0.001****
	(−2.289)	**(−2.402)**	**(−1.920)**	**(−2.094)**
Media_Att × Readability (H2)		**−0.001*****		**−0.001****
		(−2.702)		**(−2.514)**
Media_Att		**0.016****		**0.016****
		(2.245)		**(2.214)**
High_Tech × Readability (H3)			**0.002*****	**0.001*****
			(2.934)	**(2.641)**
High_Tech			**0.008**	**0.009**
			(0.493)	**(0.536)**
ROA	−0.900***	−0.894***	−0.903***	−0.896***
	(−10.551)	(−10.424)	(−10.604)	(−10.469)
SOE	−0.003	−0.002	−0.004	−0.002
	(−0.240)	(−0.135)	(−0.259)	(−0.153)
Dual	0.011	0.010	0.010	0.010
	(1.041)	(0.976)	(1.026)	(0.963)
Ln_Size	0.035***	0.027***	0.035***	0.027***
	(3.820)	(2.673)	(3.856)	(2.698)
List_Age	0.002	0.004	0.002	0.003
	(0.170)	(0.290)	(0.136)	(0.262)
Top1	−0.001***	−0.001***	−0.001***	−0.001***
	(−2.693)	(−2.596)	(−2.725)	(−2.623)
TobinQ	0.038***	0.036***	0.038***	0.036***
	(10.865)	(9.281)	(10.794)	(9.183)
All_Readability	0.000	0.000	0.000	0.000
	(0.348)	(0.331)	(0.442)	(0.421)
All_Tone	−0.162	−0.160	−0.159	−0.159
	(−1.544)	(−1.533)	(−1.514)	(−1.512)
Year, Industry	controlled	controlled	controlled	controlled
Constant Terms	−0.132	−0.038	−0.141	−0.048
	(−0.682)	(−0.188)	(−0.738)	(−0.236)
N	16484	16484	16484	16484
adj. R^2	0.085	0.086	0.085	0.086

Note: ***, **, and * indicate that the coefficient is significant at the 1%, 5%, and 10% levels, respectively; the t-value is enclosed in parentheses.

Table A2. Panel fixed effects model results after changing moderating variables measures.

Variable	(1) |Deviation|	(2) |Deviation|	(3) |Deviation|	(4) |Deviation|
Readability (H1)	**−0.056***	**−0.060***	**−0.051***	**−0.055***
	(−2.972)	**(−3.144)**	**(−2.792)**	**(−2.970)**
Media_Att × Readability (H2)		**−0.035****		**−0.033****
		(−2.383)		**(−2.278)**
Media_Att		**0.004**		**0.003**
		(0.596)		**(0.538)**
High_Tech × Readability (H3)			**0.096***	**0.091****
			(2.721)	**(2.544)**
High_Tech			**−0.017**	**−0.016**
			(−0.992)	**(−0.949)**
ROA	−0.898***	−0.917***	−0.900***	−0.919***
	(−10.530)	(−10.316)	(−10.521)	(−10.313)
SOE	−0.003	−0.005	−0.003	−0.005
	(−0.231)	(−0.359)	(−0.193)	(−0.320)
Dual	0.011	0.011	0.011	0.011
	(1.060)	(1.032)	(1.082)	(1.060)
Ln_Size	0.035***	0.035***	0.035***	0.036***
	(3.861)	(3.488)	(3.888)	(3.518)
List_Age	0.002	0.001	0.001	−0.000
	(0.173)	(0.115)	(0.054)	(−0.001)
Top1	−0.001***	−0.001***	−0.001***	−0.001***
	(−2.689)	(−2.707)	(−2.726)	(−2.743)
TobinQ	0.038***	0.039***	0.039***	0.039***
	(10.869)	(9.996)	(10.875)	(9.994)
All_Readability	0.000	0.000	0.000	0.000
	(0.187)	(0.279)	(0.290)	(0.372)
All_Tone	−0.149	−0.144	−0.143	−0.139
	(−1.421)	(−1.353)	(−1.357)	(−1.297)
Year, Industry	controlled	controlled	controlled	controlled
Constant Terms	−0.140	−0.160	−0.131	−0.153
	(−0.724)	(−0.782)	(−0.686)	(−0.756)
N	16484	16106	16484	16106
adj. R^2	0.085	0.085	0.086	0.086

Note: ***, **, and * indicate that the coefficient is significant at the 1%, 5%, and 10% levels, respectively; the t-value is enclosed in parentheses.