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How Positive Tone Amplifies Impact of Big Data-Driven Digital Transformation on Firm Value? -- An Interdisciplinary Study in Computer Science, Linguistics, and Management

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Abstract. In the information age, which is characterized by a proliferation of diverse data, big data technologies have emerged as a key driver for corporate digital transformation and improved enterprise performance. This study conducts an interdisciplinary investigation, integrating insights from computer science, linguistics, and management, to assess the importance of a positive tone in enhancing the impact of digital transformation on firm value. Advanced machine learning techniques and natural language processing algorithms are employed to analyze management discussion reports from listed Chinese companies (2007-2022). The research identifies keyword frequencies related to big data-driven digital transformation and analyses language sentiment using extensive lexicons and NLP models. Statistical models examine the reciprocal impact of digital transformation initiatives on enterprise value and the role of positive tone in reinforcing this relationship. Findings reveal significant improvements in enterprise value for enterprises engaging in big data-driven digital transformation, with positive tone amplifying these benefits. This research offers insights into synergies between technological adoption, communication strategies, and business performance.

Keywords: big data analytics, digital transformation, natural language processing, sentiment analysis, business value, machine learning

1 Introduction

With the rapid advancement of information technology, particularly the widespread adoption of the Internet, Internet of Things, cloud computing, and other technologies, the generation and collection of data have become increasingly convenient and efficient [1]. These data encompass not only traditional structured data but also semi-structured and unstructured data, exhibiting diverse characteristics. As big data application scenarios continue to expand, they are permeating every aspect of life and driving the comprehensive digital transformation of enterprises. Big data-driven digital transformation refers to an enterprise's use of big data as its core technology. This involves the implementation of advanced data analytics techniques, machine learning algorithms, and artificial intelligence systems for the collection, processing, analysis, and application of massive amounts of data. These technological implementations drive comprehensive changes in the enterprise's business processes, organizational structure, corporate culture, and other aspects [2]. This transformation aims to adapt to the evolving demands of the digital era, foster innovation in business models, and enhance overall value.

In the realm of computer science, natural language processing (NLP) techniques have emerged as powerful tools for analyzing communication in various contexts. A positive tone is characterized by optimism, energy, and confidence, can be identified and quantified using sophisticated NLP algorithms. Such statements reflect the speaker's optimistic perspective and demeanor towards various subjects, establishing a positive emotional ambiance for the audience [3]. This tone not only enhances communication effectiveness but also cultivates the interest and enthusiasm of the listener, thereby promoting positive interaction and cooperation between the parties

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involved. From a computational linguistics perspective, the utilization of positive intonation by leaders signifies their use of optimistic, confident, and positive language to portray their financial standing, operational performance, and future growth potential [4]. This tone conveys the company's satisfaction with past outcomes, optimism for the future, and anticipation of sustaining a positive development trajectory. In practice, when managers promote enterprise development through digital transformation, they often use positive language to describe the outcomes of this process, which can enhance the beneficial impacts of digital transformation.

Scholars have extensively validated the significant role of big data-driven digital transformation in enterprise development. Firstly, utilizing big data in digital transformation can greatly enhance operational efficiency [5-7]. This is achieved through the implementation of advanced data processing algorithms and real-time analytics systems. Secondly, the digital transformation facilitated by big data contributes to augmenting enterprises' innovation capabilities [8-10]. This is often realized through the application of machine learning models for predictive analytics and decision support systems. Moreover, using big data to propel digital transformation has the potential to enhance customer experience within enterprises [11-13]. This is typically accomplished through the deployment of AI-powered customer relationship management systems and personalized recommendation algorithms. Recent research validates that harnessing big data for digital transformation empowers enterprises to develop more adaptable, effective, and intelligent operational frameworks, consequently gaining a competitive edge. Despite these insights, the significant role of managers' positive tone has been overlooked, primarily due to a lack of interdisciplinary research. This gap exists at the intersection of computer science, linguistics, and management studies. It is because of the lack of interdisciplinary research. As known that, managers tend to use optimistic, confident, and positive language when reporting on digital transformation implementation and future development prospects of their organizations. This linguistic approach may either enhance or diminish the impact of digital transformation on firm value. However, this phenomenon has not been extensively validated by scholars.

To address the research gaps, the study undertakes an interdisciplinary investigation encompassing computer science, linguistics, and management. The primary objective is to assess the significance of a positive tone in augmenting the efficacy of digital transformation for enterprises. Specifically, by employing computer science and machine learning methodologies, including text mining, sentiment analysis, and neural network-based language models, a database is constructed that includes management discussion reports from publicly traded companies covering the period from 2007 to 2022. These PDF documents are transferred to TXT documents to form the text data pool. Subsequently, referring to linguistic research, an analysis of word frequency is conducted on keywords related to the digital transformation driven by big data, along with positive and negative terms from a comprehensive dictionary. The degree of digital transformation and management positive tone are measured through the application of advanced NLP techniques, including named entity recognition, topic modelling, and sentiment classification algorithms. Finally, drawing upon principles from management science, this study utilises regression analysis to explore the potential reciprocal influence of big data-driven digital transformation initiatives on improving enterprise value, as well as the potential effects of utilizing a positive tone in annual reports to enhance this phenomenon.

Subsequently, a literature review will be conducted, followed by an analysis of the research hypotheses presented in the paper. Then, the research methods and empirical results will be discussed, culminating in a comprehensive discussion and summary of the findings.

2 Literature Review

2.1 Big Data and Digital Transformation

Big data denotes a vast volume of data that exceeds the capacity of conventional software tools to efficiently for leveraging it into valuable insights for business decision-making within a reasonable time frame [14]. The significance lies not only in the vast volume of data but also in the thorough exploration and efficient utilization of data [15-16]. The four fundamental characteristics of big data, which are Volume, Velocity, Variety, and Value, along with the additional feature introduced by IBM, Veracity, collectively form the essential attributes of big data [17]. The fundamental essence of big data resides in the storage and examination of extensive datasets, while its strategic importance is found in the creation of value-enhanced data achieved by the specialized processing of significant data [18-19].

Digital transformation refers to the thorough overhaul and restructuring of an organization's strategic framework, business model, operational processes, production methods, and organizational setup through the efficient utilization of digital technology [20-21]. According to the existing literature, digital transformation consists of three distinct levels: transformation, integration, and reconstruction. "Transformation" pertains to the conversion of traditional business models, processes, products, and services into digital formats to meet the requirements of the digital era [22] "Integration" represents the overall incorporation of digital technology across all aspects of the enterprise to establish a seamless connection between digitization and business operations [23]. Reconstruction" represents a more profound level of transformation, encompassing the comprehensive reorganization and upgrading of the strategic system, organizational structure, culture, and other facets of the enterprise [24]. This process aims to establish a creative business model that is responsive to the demands of the digital era.

There is an intrinsic relationship between big data and digital transformation. On one hand, big data plays a significant role as a resource and catalyst in the process of firm digital transformation [25]. Big data, characterized by large data volumes, diverse data formats, fast processing speeds, and low value density but high business value [17], which enabling big data to provide enterprises with more comprehensive and precise business insights [26]. Through conducting analysis and mining of massive data, for instance, organizations can obtain a deeper understanding of the market and customer requirements [27]. It also enables enterprises to enhance supply chain management [28], refine product design [29], elevate customer experience [27], and facilitates digital operations and innovation [30]. On the other hand, Digital transformation, provides the foundation to the creation and utilization of big data. Engaging in digital transformation, organizations will integrate various digital technologies and tools to digitize traditional business processes, management methods, and business models. The utilization of these technologies and tools enhances enterprises' capabilities to enhance their capabilities in collecting, storing, analyzing, and utilizing diverse data and information [31]. Thus, this process establishes a robust groundwork for the creation and utilization of massive data.

2.2 Positive Tone and Positive Tone in Management

The positive connotation of intonation is primarily manifested through an optimistic, uplifting, and inspiring mode of expression [32]. It conveys a positive emotional attitude and value orientation [33]. When individuals adopt a positive tone, they typically opt for vocabulary and sentence structures that elicit positive emotions and radiate positive energy. This approach aims to imbue the listener with feelings of warmth, encouragement, and hope [34].

The existing literature has recognized that the utilization of a positive tone by a manager has various benefits. On one hand, maintaining a positive tone can enhance the company's image and reputation. By projecting a positive outlook and image for the company, a positive tone contributes to enhancing trust and goodwill among investors and the public [35]. The favorable portrayal will contribute to strengthening the company's market position and brand value, consequently drawing increased interest from investors and partners. On the other hand, maintaining a positive tone within a company can enhance internal cohesion and boost employee morale [36]. The demonstration of the company's performance outcomes and outlook can foster a positive atmosphere that boosts employee pride, a sense of belonging, and ultimately, enhances motivation and creativity among employees. The favorable environment contributes to enhancing the operational efficiency and market competitiveness of the company.

3 Research Hypothesis

3.1 Big Data-Driven Digital Transformation and Enterprise Value

The utilization of big data for digital transformation has a substantial influence on the value of enterprises. Digital transformation involves leveraging advanced digital technologies, such as machine learning algorithms and big data analytics platforms to facilitate organizational changes in business models, organizational structures, and corporate cultures within enterprise organizations [20, 21]. Enterprise value can be improved in this transformation process through the application of sophisticated data science techniques. Firstly, the efficient usage of big data can help enterprises optimize processes and allocate resources effectively [37]. By employing advanced data mining techniques and predictive analytics on massive datasets, enterprises can identify bottlenecks and inefficient resource allocation in the production and service process. This data-driven approach enables them to achieve tailored optimizations and enhance operational efficiency through the implementation of machine learning models [38]. This technological upgrading not only serves to decrease expenses but also enhances the responsiveness and adaptability of enterprises, thereby bolstering their market competitiveness. Secondly, undergoing digital transformation has the potential to enhance the quality of products and services through the application of artificial intelligence and data analytics [39]. For instance, by extensively collecting and analyzing consumer data using natural language processing and sentiment analysis techniques, enterprises can enhance their comprehension of consumer behaviors and demands. Adopting a consumer-centric philosophy, powered by advanced analytics and machine learning algorithms, helps organizations cultivate long-term and stable customer relationships, as well as enhance brand image and foster loyalty. Thirdly, big data plays a significant role in driving changes within enterprises' organization and culture during the process of digital transformation [40]. Engaging in digital transformation necessitates that organizations cultivate a more robust data-oriented approach and enhance their data-driven competencies. As a result, it forces companies to strengthen internal collaboration and communication channels, promoting the development of a more transparent and innovative organizational culture. Accordingly, this study proposes:

H1: Big data-driven digital transformation, facilitated by advanced analytics and machine learning techniques, can promote enterprise value.

3.2 Positive Tone, Big Data-Driven Digital Transformation and Enterprise Value

A positive tone is conducive to enhance the beneficial impact of digital transformation on business value. When corporate managers present the results and prospects of digital transformation using a positive tone, this optimistic and affirmative approach can better express the beneficial impact of digital transformation to internal employees and external investors [41]. Specifically, firstly, a positive tone, as measured by sophisticated sentiment analysis algorithms, emphasizes the potential of digital transformation to enhance efficiency, optimize business processes, and improve the customer experience. By highlighting the innovations and enhancements brought by digital transformation, enterprises can improve employee confidence and engagement in the process, thereby promoting the adoption of digital transformation [42]. Positive sentiment, as detected by machine learning-based text classification models, is more likely to improve digital participation [43]. On the other hand, a positive tone can also highlight the excellent effects of digital transformation on the future progress of the enterprise. Companies have the ability to articulate how digital transformation can attract the interest of investors and partners by introducing new avenues of growth, expanding market reach, improving the quality of products and services, and increasing competitiveness. This optimistic tone, when consistently detected through longitudinal sentiment analysis of corporate communications, has the potential to attract additional external resources and assistance for enterprises, thereby expediting the benefits and value creation brought by digital transformation. To quantify and analyze these relationships, this study employs advanced natural language processing techniques, including deep learning models for sentiment analysis and topic modelling, to process large volumes of corporate communications. The resulting insights are then integrated with financial performance data using sophisticated machine learning algorithms to model the complex interactions between communication tone, digital transformation initiatives, and enterprise value. Accordingly, this study proposes the following hypotheses, which are depicted in the conceptual model illustrated in Fig. 1.

H2: Positive tone, as measured through advanced NLP and sentiment analysis techniques, reinforces the value drive of digital transformation.

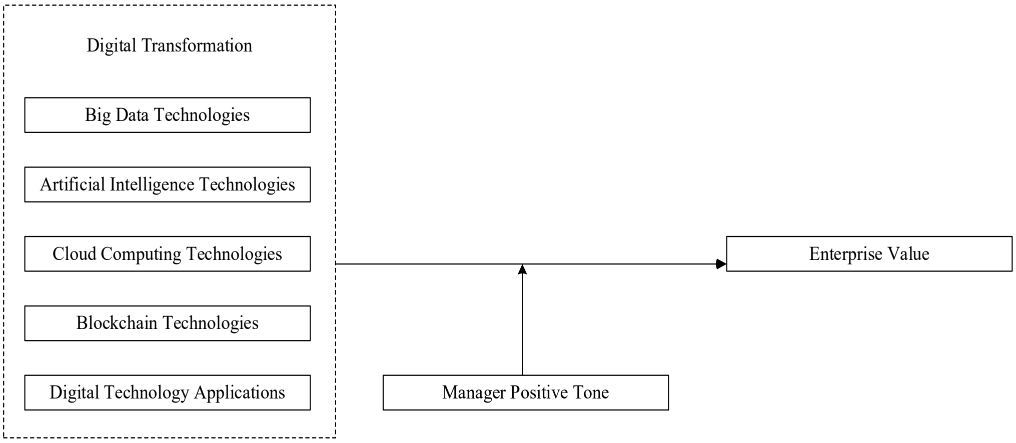

Fig. 1. Concept model

4 Methodology

4.1 Data Resource and Measurements of Variables

Data Resource and Measurements of Big Data-Driven Digital Transformation. This study selects management discussion and analysis (MD&A) sections from the annual reports of listed companies as the primary research sample. Specifically, the sample spans from 2007 to 2022, capturing a wide range of economic cycles, regulatory changes, and technological advancements.

The selection process involves the following steps:

a) Identification of Relevant Companies: Publicly listed companies across major stock exchanges are identified. The selection process utilizes machine learning algorithms to focus on companies with substantial market capitalization and significant digital transformation initiatives, based on predefined criteria and textual analysis of company reports.

b) Data Collection: Annual reports are sourced from reputable financial databases and company websites using automated web scraping techniques. The MD&A sections are extracted using natural language processing algorithms and converted into a structured text format for analysis.

c) Inclusion Criteria: Companies are included based on the availability and completeness of their annual reports over the selected period, determined through automated data quality checks. Firms with missing or incomplete MD&A sections are excluded using anomaly detection algorithms to ensure data consistency.

d) Industry Diversification: To ensure a comprehensive analysis, the sample includes companies from diverse industries such as technology, healthcare, finance, manufacturing, and consumer goods. This diversification is achieved through automated industry classification algorithms and cluster analysis techniques.

Furthermore, the study employs a stratified sampling technique implemented through machine learning algorithms to ensure that the sample adequately represents different market conditions and company sizes. By doing so, the research mitigates potential biases and enhances the generalizability of the findings. The detailed process of sample selection and data preprocessing is illustrated in Fig. 2, which includes a flowchart of the computational steps involved.

In identifying key terms associated with enterprise digital transformation, this study employs advanced natural language processing techniques, including topic modelling and named entity recognition, consulting seminal literature on the subject [44]. This consolidation and categorization of specific keywords relevant to digital transformation result in the creation of a feature word map depicted in Fig. 2, which is generated using data visualization techniques.

The extracted textual data is then processed using a combination of text mining techniques, including tokenization, stemming, and lemmatization, to prepare it for further analysis. The processed text is then subjected to frequency analysis and term frequency-inverse document frequency (TF-IDF) calculations to identify the most relevant terms related to digital transformation. Overall, the rigorous sample selection and data processing procedures, underpinned by advanced big data and machine learning techniques, ensure the robustness of this study. This enables a thorough investigation into how positive managerial tone and digital transformation initiatives influence enterprise value, leveraging the power of computational linguistics and data science methodologies.

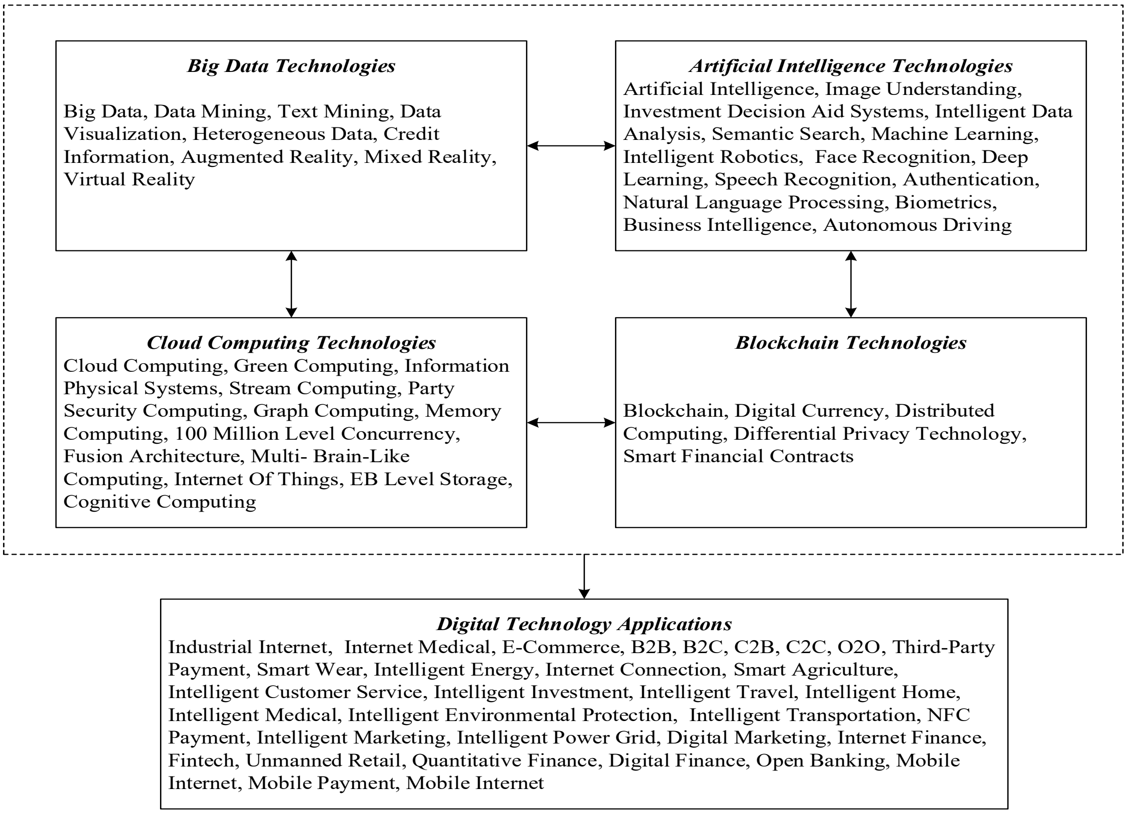

Fig. 2. Keywords related to big data-driven digital transformation

Data Resource and Measurements of Management Positive Tone. The measurement of management positive tone follows a method similar to that used for measuring digital transformation, with the primary difference being the keywords utilized in the statistics. Loughran and McDonald conducted a seminal study using 10-K filings from 1994 to 2008, finding that the Harvard Dictionary's definition of negative words, commonly used in prior tone studies, was not entirely suitable for analyzing the tone of financial reports [45]. Consequently, they developed alternative negative and positive word lists, along with additional lists that better reflect tone in financial text.

Building upon the financial sentiment English word list provided by Loughran and McDonald and following the methodology of Zeng et al., this study employed machine translation algorithms to translate all the English words using Youdao Dictionary and Kingsoft Dictionary [45, 46]. In instances where an English word corresponded to multiple Chinese words, a word sense disambiguation algorithm was applied to retain all possible translations, ensuring comprehensive coverage of tone sentiment words in Chinese financial reports. The final word list comprised 22,549 negative words and 5,934 positive words. Typical negative words include "litigation," "termination," "discontinued," "penalties," "misstatement," "misconduct," "forfeiture," "serious," "noncompliance," and "deterioration." Words in the positive list, such as "achieve," "attain," "efficient," "improve," "profitable," and "upturn," are typically used to convey a positive tone.

After compiling the Chinese word list, the Python open source "Jieba" Chinese word segmentation module, which utilizes a hybrid approach combining a pre-defined dictionary and statistical model for unknown word recognition, was employed to automatically segment the full text of the annual reports. Subsequently, word frequency statistics were calculated using distributed computing techniques to handle the large volume of text data efficiently. Careful consideration was given to the phenomenon of semantic reversal, implementing a context-aware sentiment analysis algorithm. Specifically, if a positive word is immediately followed by a negative word, it is counted as a negative word, and vice versa. This approach ensures that the sentiment analysis accurately reflects the intended tone of the management's language.

Following He & Wan [47], the overall tone of the management is measured using the following formula (1):

$$\text{TONE} = \frac{\text{Positive} - \text{Negative}}{\text{Positive} + \text{Negative}} \tag{1}$$

where "Positive" represents the count of positive words in the MD&A section, and "Negative" indicates the number of negative intonation words. TONE thus indicates the overall optimistic tone of the management.

Data Resource and Measurements of Enterprise Value. Return on Assets (ROA) serves as a critical metric for evaluating a company's performance due to its ability to indicate the efficiency and profitability of asset utilization. ROA is instrumental in assessing the long-term value and growth prospects of a company, as it reflects how effectively a company is converting its investments into net income. By focusing on ROA, investors can gain a deeper understanding of the company's sustained earnings capacity and its potential for long-term growth. The formula for calculating ROA is as follows:

$$\text{ROA} = \frac{\text{Net Profit}}{\text{Average Balance of Total Assets}} \tag{2}$$

This metric provides a comprehensive measure of the company's ability to generate profits from its assets, making it a valuable indicator for both internal management and external stakeholders. To enhance the accuracy and reliability of this measure, advanced data analytics techniques are employed to preprocess and clean the financial data, ensuring consistency and addressing any outliers or anomalies.

In addition to ROA, this study incorporates a machine learning-based feature selection process to identify a set of control variables that might influence enterprise value. Lasso regression is a regularization technique that performs variable selection, effectively shrinking the coefficients of less important features to zero. By applying Lasso regression to a comprehensive set of potential control variables, we can identify the most relevant variables that have a significant impact on enterprise value. Random Forest, on the other hand, constructs multiple decision trees and aggregates their results to make predictions. The importance of each variable is determined by measuring the increase in prediction error. Variables with higher importance scores are considered more influential in predicting enterprise value. By combining the results from both Lasso regression and Random Forest importance analysis, we obtain a robust set of control variables that are most likely to impact enterprise value.

The control variables in Table 1 encompass various financial and operational metrics that may influence a firm's value. Firm size and age are included as they can impact a firm's resources, processes, and performance [48]. The Asset-Liability Ratio reflects financial risk and investment capacity [49], while investment level controls for resources available for value-enhancing initiatives [50]. Liquidity ratios and ownership structure, particularly state ownership, can influence firm value, decision-making, and resource allocation [51, 52]. Finally, Revenue Growth Rate and Growth Rate of Total Assets control for firm growth, a key driver of firm value [53]. The inclusion of these control variables ensures a more robust and reliable analysis by mitigating the potential confounding effects that could distort the relationship between digital transformation, managerial tone, and enterprise value.

Table 1. Control variable measurements

Variables	Abbreviation	Measurements
Firm Size	Size	Total Assets Per Year; Natural Log Processing
Firm Age	Age	Ln (Observed Year - Established Year +1)
Asset-Liability Ratio	Lev	Total Liabilities /Total Assets

Investment Level	Invest	(Cash Paid for The Acquisition Of Fixed Assets, Intangible Assets, And Other Long-Term Assets) / Total Assets At The Beginning Of The Period
Liquidity Ratio	Liquid	Current Assets/Current Liabilities
State-Owned Enterprise or Not	SOE	1 For State-Owned Enterprises; 0 For Others
Revenue Growth Rate	Growth	Current Year Operating Income / Previous Year Operating Income -1
Growth Rate of Total Assets	Asset_Growth	Total Assets of This Year/Total Assets of Last Year -1

4.2 Summary Statistics

The summary statistics of the large dataset were computed using advanced statistical libraries and big data processing frameworks. Descriptive analytics and data visualization techniques revealed insights into the distribution and characteristics of the variables. Detailed results are shown in Table 2. The mean Return on Assets (ROA) is 0.039, with a standard deviation of 0.095, indicating a concentration of data points around the mean. The average digital transformation score is 0.755, with a standard deviation of 1.131, highlighting variability across companies. The mean value of positive tone in management discussion and analysis (MD&A) sections is 0.349, with a standard deviation of 0.131. Interactive data visualizations and dimensionality reduction techniques were used to explore relationships between variables and uncover patterns in the data. These computational methods enhance the accuracy and depth of the analysis, providing a comprehensive overview of the sample characteristics.

Table 2. Summary statistics results

Variables	Obs	Mean	SD	Min	Median	Max
ROA	40248	0.039	0.095	-1.859	0.038	10.530
DIT	40248	0.755	1.131	0.000	0.000	5.938
TONE	40248	0.349	0.117	-0.321	0.356	0.798
Size	40248	22.162	1.328	14.158	21.977	28.636
Age	40248	2.873	0.362	0.693	2.944	4.174
Lev	40248	0.440	0.657	0.007	0.430	124.022
Invest	40248	0.067	0.333	0.000	0.040	60.969
Liquid	40248	2.461	3.595	0.008	1.610	204.742
SOE	40248	0.383	0.486	0.000	0.000	1.000
Growth	40248	4.042	675.075	-2.733	0.107	1.35e+05
Asset_Growth	40248	0.271	3.790	-0.993	0.093	379.546

4.3 Construction of Models

Based on the hypotheses proposed, this paper constructs the following test models (Formulas 3 and 4):

$$ROA_{i,t} = \alpha + \beta_1 \times DIT_{i,t} + \Sigma Control + \Sigma year + \Sigma ind + \varepsilon \quad \textbf{(3)}$$

$$ROA_{i,t} = \alpha + \beta_1 \times DIT_{i,t} + \beta_2 \times TONE_{i,t} + \beta_3 \times DIT_{i,t} \times TONE_{i,t} + \Sigma Control + \Sigma year + \Sigma ind + \varepsilon \quad \textbf{(4)}$$

Where $ROA_{i,t}$ represents the return on assets (enterprise value) of company *i* in year *t*, $DIT_{i,t}$ indicates the digital transformation level of company *i* in year *t*. TONE indicates the overall optimistic tone of the management. A larger value of TONE signifies a more positive management tone. Additionally, ∑Control denotes the control variables included in the model to account for other influencing factors. ∑ year and ∑ind represent year and industry fixed effects, respectively. ε is the disturbance term capturing unobserved heterogeneity. The process of constructing and testing these models is illustrated in Algorithm 1.

Algorithm 1. Construction and testing of regression models

1. Begin

    1. Initialize: Load datasets containing variables for ROA, digital transformation (DIT), positive tone (TONE) and control variables.

    2. Define: Model variables and specifications.

        2.1 Set dependent variable $ROA_{i,t}$.

        2.2 Set independent variables $DIT_{i,t}$ and $TONE_{i,t}$.

        2.3 Include interaction term *D* $DIT_{i,t}$ and $TONE_{i,t}$.

        2.4 Include control variables *Control*.

        2.5 Define fixed effects for year ∑ year and industry ∑ind .

    3. Specify Models:

        3.1 **Model 1**: Test direct effect of digital transformation.

$$ROA_{i,t} = \alpha + \beta_1 \times DIT_{i,t} + \Sigma Control + \Sigma year + \Sigma ind + \varepsilon$$

        3.2 **Model 2**: Test interaction effect of positive tone.

$$\begin{aligned} ROA_{i,t} &= \alpha + \beta_1 \times DIT_{i,t} + \beta_2 \times TONE_{i,t} \\ &\quad + \beta_3 \times DIT_{i,t} \times TONE_{i,t} + \Sigma Control + \Sigma year + \Sigma ind + \varepsilon \end{aligned}$$

    4. Estimate: Use regression analysis to estimate coefficients.

        4.1 For Model 1:

        Run regression on with ROAi,t with DITi,t, control variables.

        4.2 For Model 2:

        Run regression on with $ROA_{i,t}$ with $DIT_{i,t}$, TONEi,t, interaction term and control variables.

    5. Evaluate: Assess statistical significance of coefficients.

        5.1 Calculate: P-values.

        5.2 Determine: If coefficients are significant at conventional levels.

    6. Validate: Ensure robustness of results.

        6.1 Conduct: Robustness checks (e.g., using alternative dependent variables).

        6.2 Perform: Endogeneity tests using instrumental variables.

2. End

The first model (Formula 3) established a baseline by examining the direct relationship between digital transformation and enterprise value. The second model (Formula 4) extends this by incorporating the managerial tone variable and an interaction term between tone and digitalization to explore the moderating effect of positive managerial tone on the relationship between digitalization and ROA.

These models are designed to empirically validate the proposed hypotheses by isolating the effect of digital transformation and managerial tone on enterprise value, while controlling for potential confounders through the inclusion of fixed effects and control variables. Notably, this approach is enhanced by the integration of machine learning techniques, enabling the capture of non-linear relationships and interactions that might be overlooked by traditional linear regression methods. For instance, a linear regression model might assume a straightforward, proportional relationship between these variables. However, an advanced algorithm like a Random Forest can detect complex, non-linear relationships between digital transformation initiatives and firm performance that a linear regression might miss. Furthermore, machine learning algorithms like Gradient Boosting can identify intricate interaction effects. For example, it might uncover that the positive impact of digital transformation on firm value is amplified when combined with a positive managerial tone, but only up to a certain threshold, after which the effect diminishes. Such a nuanced relationship would be difficult to capture with traditional linear regression methods. This combination of empirical models, control variables, and advanced machine learning algorithms ensures a nuanced analysis of the intricate interplay between digital transformation initiatives and managerial communication strategies in influencing firm performance.

5 Empirical Results

5.1 Regression Analysis

The regression analysis results are presented in Table 3. Columns (1) and (2) display the relationship between digital transformation and enterprise value, with and without the addition of control variables, respectively. The coefficients are 0.002 and 0.001, both statistically significant at the 1% level. This indicates a robust positive relationship between digital transformation and enterprise value, suggesting that as enterprises further their digital transformation efforts, their enterprise value correspondingly increases. Therefore, H1 is supported.

Furthermore, the analysis reveals that a positive managerial tone significantly strengthens the positive correlation between digital transformation and enterprise value enhancement. The interaction term coefficients are 0.020 and 0.018, statistically significant at the 5% level and 1% level, respectively. These results indicate that a positive tone plays a significant moderating role to effectively enhance the impact of digital transformation, significantly promoting an increase in enterprise value. Hence, H2 is supported.

To further validate these results, we employed ensemble methods such as Random Forests and Gradient Boosting Machines (GBM). These techniques allowed us to capture complex, non-linear relationships in the data and provided additional insights into feature importance. The GBM analysis used the same variables, assessed feature importance, particularly for the interaction term, as well as compared directionality and relative importance of variables with linear regression results. The GBM results corroborated our linear regression findings. These additional analyses strengthen our confidence in the results presented in Table 3. Additionally, a series of robustness checks using alternative model specifications and variable definitions were conducted. This included quantile regression to examine the effects across different points of the enterprise value distribution, and panel data methods to account for time-invariant unobserved heterogeneity.

Table 3. Regression analysis results

	(1) ROA		(2) ROA		(3) ROA		(4) ROA	
	P-value	t	P-value	t	P-value	t	P-value	t
DIT	0.002***	2.591	0.001***	2.841	-0.010***	-2.823	-0.009***	-4.626
Size			0.004***	3.785			0.003***	2.717
Age			-0.014***	-8.137			-0.010***	-6.108
Lev			0.064***	3.296			0.066***	3.558
Invest			0.008	0.944			0.007	0.926
Liquid			0.005***	6.246			0.005***	6.440
SOE			-0.013***	-12.713			-0.015***	-15.297
Growth			-0.000	-1.038			-0.000**	-2.047
Asset_Growth			0.001**	2.023			0.001**	2.364
Interaction					0.020**	2.524	0.018***	3.655
TONE					0.166***	8.309	0.187***	28.807
_cons	0.037***	41.993	-0.053**	-2.529	-0.018**	-2.373	-0.098***	-4.980
Industry&Year FE	√		√		√		√	
N	40248		40248		40248		40248	
adj. R2	0.013		0.224		0.057		0.277	

* p < 0.1, ** p < 0.05, *** p < 0.01.

5.2 Further Analysis

Enterprise Nature Heterogeneity. State-owned enterprises (SOEs) typically possess advantages in terms of capital, technology, and talent, enabling them to undertake more extensive and profound digital transformation initiatives. Upon successful implementation, this transformation frequently results in substantial benefits, such as the optimization of internal management processes, enhancement of operational efficiency, and improvement of organizational stability and sustainability. Consequently, SOEs may experience a more significant enhancement in enterprise value following digital transformation to a certain degree. To investigate this heterogeneity, advanced machine learning techniques, including ensemble methods and deep learning models were employed, to capture complex patterns in the data that might not be apparent through traditional statistical approaches.

Referring to Table 4, the results in Columns (1) and (2) verify this heterogeneity. The positive relationship between digital transformation and firm value is statistically significant only for SOEs. This finding underscores the potential for greater value enhancement in SOEs due to their resource advantages and capacity for comprehensive digital initiatives.

However, the analysis reveals that the positive role of managerial positive tone is significant only for non-SOEs. This indicates that in non-SOEs, a positive managerial tone can effectively amplify the benefits of digital transformation. The differential impact suggests that while SOEs may rely more on their inherent advantages, non-SOEs benefit more from positive managerial communication in leveraging digital transformation for value enhancement.

Table 4. Heterogeneity analysis based on enterprise nature

	(1) Non-SOE		(2) SOE		(3) Non-SOE		(4) SOE	
	P-value	t	P-value	t	P-value	t	P-value	t
DIT	0.000	0.733	0.002***	3.762	-0.010***	-4.076	0.000	0.098
Size	0.006***	4.878	0.012***	26.922	0.004***	3.557	0.011***	26.015
Age	-0.017***	-8.534	0.003*	1.870	-0.014***	-6.987	0.006***	3.517
Lev	0.070***	4.761	-0.167***	-32.427	0.072***	5.104	-0.158***	-31.797
Invest	0.005	0.658	0.081***	6.232	0.003	0.578	0.078***	6.111
Liquid	0.004***	6.152	-0.001**	-2.002	0.004***	6.369	-0.001	-1.432
Growth	-0.000	-1.428	-0.000***	-4.598	-0.000**	-2.353	-0.000***	-4.665
Asset_Growth	0.001**	1.984	0.000	0.300	0.001**	2.286	0.000	0.418
Interaction					0.016***	2.670	-0.000	-0.058
TONE					0.218***	24.336	0.108***	20.102
_cons	-0.085***	-3.304	-0.174***	-16.234	-0.128***	-5.197	-0.202***	-18.719
Industry&Year FE	√		√		√		√	
N	24852		15396		24852		15396	
adj. R2	0.294		0.257		0.346		0.293	

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Industrial Characteristics Heterogeneity. Digital transformation is frequently associated with the fundamental business and technological competencies of high-tech firms. These companies often possess robust research and development (R&D) capabilities and a technological foundation that enables them to promptly embrace and adapt to emerging digital technologies and tools. High-tech enterprises typically have the infrastructure, skilled talent, and financial resources to support rapid and comprehensive digital transformation initiatives.

Referring to Table 5, the results in Columns (1) and (2) verify this heterogeneity. The positive relationship between digital transformation and firm value is statistically significant only in high-tech companies. However, the results in Columns (3) and (4) indicate that the positive role of managerial positive tone is significant for both high-tech and non-high-tech companies. This suggests that regardless of the industrial characteristics, a positive managerial tone can effectively enhance the benefits of digital transformation. For high-tech companies, this can further amplify their existing advantages, while for non-high-tech companies, positive managerial communication can play a critical role in overcoming some of the inherent challenges they face during digital transformation.

Table 5. Heterogeneity analysis based on industrial characteristics

	(1) Non-high-tech		(2) High-tech		(3) Non-high-tech		(4) High-tech	
	P-value	t	P-value	t	P-value	t	P-value	t
DIT	0.001	0.869	0.001**	2.095	-0.010***	-3.480	-0.008***	-2.916
Size	0.015***	24.560	0.004***	3.192	0.014***	23.906	0.003**	2.126
Age	-0.000	-0.156	-0.016***	-5.884	0.001	0.875	-0.011***	-4.296
Lev	-0.172***	-32.034	0.071***	4.980	-0.161***	-31.924	0.072***	5.335
Invest	-0.005	-1.028	0.078***	2.933	-0.005	-1.071	0.064**	2.487
Liquid	-0.002***	-7.464	0.005***	5.502	-0.001***	-7.158	0.005***	5.678
SOE	-0.003***	-3.199	-0.019***	-12.768	-0.006***	-5.726	-0.020***	-14.099
Growth	-0.000***	-2.903	-0.000	-1.041	-0.000***	-3.385	-0.000	-0.974
Asset_Growth	0.002***	3.847	0.000	0.370	0.002***	3.907	0.000	0.930
Interaction					0.021***	3.050	0.012*	1.948
TONE					0.119***	17.668	0.214***	24.992
_cons	-0.221***	-15.443	-0.046*	-1.788	-0.240***	-16.597	-0.100***	-4.033
Industry&Year FE	√		√		√		√	
N	17223		23025		17223		23025	
adj. R2	0.203		0.332		0.245		0.380	

* p < 0.1, ** p < 0.05, *** p < 0.01.

5.3 Robustness Tests

Instrumental Variable Test. This study employs the level of digital transformation of peer companies within the same industry and province in the same year as an instrumental variable to perform an endogeneity test. The primary aim is to address potential endogeneity issues that could arise. The utilization of instrumental variables is grounded in a specific rationale: when a variable (instrumental variable) exhibits a strong correlation with endogenous explanatory variables (such as a company's digital transformation level) but not with the error term, it becomes viable for substituting the endogenous explanatory variables. This substitution effectively mitigates the impact of endogeneity on the model estimates.

In this instance, the level of digital transformation among other companies within the identical industry and province in the same year is selected as the instrumental variable. This choice is made on the basis that it could be associated with the focal company's digital transformation level. However, as it relies on data from other companies, it is not correlated with the target company's error term, thus satisfying the requirements for a valid instrumental variable.

The results of this instrumental variable approach are presented in Table 6. As shown in Columns (1) and (2) of Panel A, the instrumental variable is positively related to digital transformation, and the coefficient of digital transformation (DIT) on return on assets (ROA) is significant at the 1% level. This finding indicates that the instrumental variable effectively captures the variations in digital transformation, thereby validating its use. The robustness of these results confirms that the positive relationship between digital transformation and enterprise performance is not driven by endogeneity issues.

Table 6. Robustness analysis

	(1) DIT		(2) ROA		(3) Gross_Profit		(4) ATO	
	Panel A				Panel B		Panel C	
	P-value	t	P-value	t	P-value	t	P-value	t
DIT			0.010***	5.350	0.006***	4.958	0.017***	5.953
Size	0.061***	14.570	0.017***	46.687	-0.009***	-4.573	0.035***	11.687
FirmAge	-0.129***	-8.400	-0.002	-1.336	-0.025***	-7.541	-0.001	-0.141
Lev	-0.132***	-4.690	-0.194***	-85.571	-0.022	-1.140	0.015	0.916
Invest	-0.039**	-2.470	0.008***	5.959	0.013	1.538	-0.007	-0.449
Liquid	-0.001	-0.470	-0.001***	-9.164	0.009***	6.796	-0.011***	-3.486
SOE	-0.162***	-15.030	-0.006***	-6.158	-0.044***	-14.286	0.032***	5.010
Growth	0.000	0.030	-0.000	-0.314	-0.000	-0.043	0.000***	2.674

AssetGrowth	0.003**	1.910	0.001***	4.944	0.000	0.033	0.003	1.547
IV	0.531***	43.260						
_cons	-0.916***	-8.760	-0.217***	-25.336	0.549***	12.437	-0.109	-1.354
Industry&Year FE	√		√		√		√	
N	38765		38765		40245		40248	
adj. R2	0.386		0.196		0.110		0.159	

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Substitute the Measurements of Explained Variable. To enhance the reliability and stability of the research findings, it is crucial to modify the measurement method of the explained variables for robustness testing.

In this study, we substitute the original explained variable with alternative financial performance indicators to validate the robustness of the results. Specifically, we use margin on sales (Gross_Profit) and total assets turnover rate (ATO) as alternative measures. The equations for Gross_Profit and ATO are shown in equations (5) and (6), respectively:

$$\text{Gross\_Profit} = \frac{\text{Operating Income} - \text{Operating cost}}{\text{Operating Income}} \tag{5}$$

$$\text{ATO} = \frac{\text{Operating Income}}{\text{Average Total Assets}} \tag{6}$$

The results of these robustness tests are presented in Columns (3) and (4) of Panel B and Panel C of Table 6. The findings indicate that the coefficient of digital transformation (DIT) on both Gross_Profit and ATO are statistically significant at the 1% level. These robustness tests confirm that the positive relationship between digital transformation and enterprise performance remains consistent even when different financial performance indicators are used. This strengthens the confidence in the study's conclusions and demonstrates the robustness of the empirical results.

6 Conclusions

6.1 Theoretical Contributions

This research integrates linguistics with computer science and management, offering significant theoretical implications. The established relationship between computer science and management is enhanced by linguistic insights, particularly in natural language processing and sentiment analysis. This integration facilitates better understanding of information flow and communication within organizations.

Moreover, the integration of linguistics introduces novel research perspectives to computer science. For example, in the field of natural language processing, linguistic research can help us better understand the structure and rules of language, and thus develop more accurate and intelligent technologies such as text processing, speech recognition, and machine translation. These technological advancements not only augment the application value of computer science but also provide linguistics with richer datasets and more sophisticated analytical tools, such as deep learning models for language understanding and generation.

In general, this interdisciplinary approach bridges gaps between the technical and human elements of organizational studies, offering a more holistic understanding of enterprise dynamics.

6.2 Practical Contributions

Firstly, enterprises should leverage big data technology for digital transformation to enhance their value. By investing in advanced analytics and machine learning algorithms, companies can improve customer experience, expand business scope, and adapt to market competition. It's crucial for enterprises to strengthen their digital capabilities and proficiency through continuous investment and effort in digital transformation.

Secondly, a positive tone in communication can significantly reinforce the beneficial impact of digital transformation on increasing enterprise value. Managers should use positive language to describe their vision, goals, and the meaning of this transformation in both internal and external communications. This approach can encourage employees to actively participate in digital technology training and strengthen investor confidence. Clear and optimistic communication about the progress and outcomes of digital transformation initiatives, supported by data-driven insights and visualizations, can enhance stakeholder engagement.

Thirdly, emphasizing the strategic benefits and long-term value generated by digital transformation efforts is crucial. Managers should highlight successful case studies and tangible improvements, quantified through key performance indicators and visualized using interactive dashboards and data storytelling techniques. This approach can illustrate the positive impacts of digital initiatives and build momentum for ongoing transformation efforts, fostering a supportive environment among employees and confidence among investors.

6.3 Limitations

This study has several limitations related to its methodology and scope. The text analysis methods used for examining digital transformation and managers' positive intonation may be constrained by the accuracy and comprehensiveness of keyword selection. Biased or incomplete keyword data could lead to skewed analysis results, affecting the accurate assessment of digital transformation extent and managers' positive attitudes. Moreover, these methods may struggle to capture the nuances and context of managerial language, potentially oversimplifying tone analysis and missing subtle yet significant aspects of communication impact. Incorporating sentiment analysis at the sentence level and word embedding techniques could further enhance the precision of tone measurement.

The sample selection presents another limitation, as the study focuses solely on listed companies, excluding non-listed firms. This approach may not provide a complete picture of the broader market impact, as unlisted companies play a crucial role in shaping competitive environments and consumer well-being. The temporal scope of the study also limits the generalizability of findings, as it may not fully capture long-term trends and the evolving nature of digital transformation practices in light of rapid technological advancements.

Lastly, the reliance on publicly available documents may omit important internal information not disclosed in official reports. The exclusion of confidential data, internal communications, and strategic decisions could lead to an incomplete analysis of the phenomena under study. Future research should aim to address these gaps to ensure a more robust and comprehensive understanding of digital transformation and the impact of managerial communication.

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