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Managerial Myopia and Digital Transformation in Manufacturing: A Text Mining Approach Based on the BERT-LDA Model

Feng HU, Jianchao LIU, Yingtong CHEN*

Abstract: In the era of digital economy, digital transformation has become an inevitable path for manufacturing enterprises to achieve high-quality development. However, not all managers of manufacturing enterprises have a long-term and sustainable development perspective. Drawing on MD&A reports from 415 Chinese manufacturing enterprises, this study applies a BERT-LDA text mining model to analyze how managerial myopia influences digital transformation. The research results reveal that: (1) The more terms related to "myopic perspective" are disclosed in MD&Atext data, the more effectively it can reflect the inherent temporal and spatial managerial myopia traits; (2) The impact of managerial myopia on the digital transformation of manufacturing enterprises is reflected in six major dimensions: short-term performance orientation suppressing R&D investment, traditional business reliance restricting the transformation vision, current indicator focus squeezing long-term projects, specific project management neglecting system transformation, existing market reliance weakening long-term layout, and short-term cash flow control reducing transformation investment. These six dimensions together constitute the resistance to the digital transformation of manufacturing enterprises. This paper comprehensively applies empirical analysis methods such as text mining, sentiment analysis and topic clustering to study the digital transformation of manufacturing enterprises, providing references and inspirations for future research in related fields. Meanwhile, this paper also broadens the analysis of the consequences of myopic behaviors of managers, which has important practical implications for the appointment of high-level management talents in enterprises and the supervision of enterprises and the government.

Keywords: deep learning; digital transformation; managerial myopia; manufacturing enterprises; text mining

1 INTRODUCTION

The development and application of new-generation information technologies such as the Internet of Things, big data and cloud computing can not only drive the growth of emerging digital industries within the industrial chain, but also promote the transformation of traditional industries through the "catfish effect", injecting huge impetus into global economic growth. In traditional manufacturing industries, manufacturing enterprises have gradually formed brand-new production and business models by deeply integrating high-tech such as information and communication technology and artificial intelligence with traditional manufacturing. The contents and methods of organizational management in manufacturing enterprises have undergone significant changes [1-3]. Against this backdrop, the digital transformation of enterprises is not only the core for enhancing their long-term value creation and sustainable development, but also the key to promoting high-quality national development and contributing to global economic growth.

Senior managers are responsible for formulating strategic directions, making major decisions and guiding the company's development. They are the helmsmen of the enterprise's development strategy and play a crucial role in the digital transformation and sustainable development of the enterprise. According to the Upper Echelons theory [4], the personal traits of managers will affect their perception of the future development direction of the enterprise, determine their behaviors and strategic choices, and ultimately affect the goals, behaviors and results of the enterprise. Therefore, the traits of managers are bound to have a significant impact on important strategic decisions such as the digital transformation of manufacturing enterprises. In the existing literatures, academic research on the traits of managers mainly focuses on demographic characteristics such as gender, educational background, work experience and values [5]. Few scholars have paid attention to the impact of managerial myopia traits on the strategic choices of enterprises' digital transformation. Among the limited literature on managerial myopia, the impact of managerial myopia on the financial performance of digital transformation is also studied through linear regression models.

In view of these, we have crawled 4,816 valid annual report data from 415 listed Chinese manufacturing enterprises. Through data processing, technology selection and model evaluation, we ultimately chose the BERT-LDA model to explore how managerial myopia influences digital transformation. The research findings reveal that the terms related to "myopic perspective" disclosed in the annual report can effectively reflect the inherent myopia traits of managers. Moreover, managerial myopia significantly hinders the digital transformation of listed Chinese manufacturing enterprises. This paper broadens the analysis of the behavioral consequences of managerial myopia, which has significant practical implications for the appointment of high-level management talents in enterprises and the supervision of enterprises and the government. Meanwhile, this paper introduces the deep learning and text mining methods based on the BERT-LDA model into the study of managerial myopia and the digital transformation of listed Chinese manufacturing enterprises. It provides a reference and inspiration for future research in this field.

The possible contributions of this paper lie in: (1) Introducing text mining and deep learning methods into the research of managerial myopia, discovering many new text indicators that can directly measure managerial myopia, providing an important reference basis for the quantification of managerial myopia; (2) Link managerial myopia with the digital transformation of enterprises, analyze the impact of managers' traits on the formulation of digital transformation strategies for manufacturing enterprises, and enrich the research on managers' traits and corporate strategies; (3) Based on the BERT-LDA model, this paper deeply analyzes the possible obstacles and predicaments that manufacturing enterprises may encounter in their digital transformation as reflected in the MD&A, and proposes possible solutions to these predicaments, providing intellectual support for enterprises to accelerate their digital transformation process and move towards high-quality development.

2 RELATED WORK

2.1 Digital Transformation

Conceptually, digital transformation refers to the application of digital technologies by enterprises to achieve a thorough change in operational efficiency and business performance [1]. As a typical representative of global traditional industries and a micro focus of current digital economic development, digital transformation of manufacturing enterprises has become a hot topic in recent years and attracted high attention from governments, industries and academia around the world. For instance, GE of the United States was the first to launch the Predix industrial Internet service platform, SanyGroup of China has built the Root Cloud platform, Siemens of Germany has introduced the MindSphere ecosystem, and ABB of Switzerland has launched the ABB Ability cloud service platform, etc. These cloud service platforms not only provide cloud services based on the Internet of Things and big data for enterprises in various industries, but also offer assistance to machine manufacturers, financial institutions, property owners, users, after-sales service providers, and government regulatory authorities in areas such as equipment management, fault management, IOT presentation, and asset management. At the same time, they connect with various industry software, hardware, and communication providers for in-depth cooperation. Form an ecological effect.

Current research on enterprise digital transformation mainly focuses on the influencing factors of enterprise digital transformation and the economic consequences it brings. In terms of the research on the influencing factors of enterprise digital transformation, existing studies indicate that an enterprise's digital transformation not only requires a strong ability to integrate digital technology resources on its own, but is also affected by the external macro environment, market environment and stakeholders, etc. The influencing factors of digital transformation mostly focuses on discussing the organizational structure, digital technology, and business model reengineering [6, 7]. In terms of the economic consequences brought about by digital transformation, existing research has found that digital transformation can not only enhance the integration of digital information resources [8] and the degree of enterprise supply chain integration [9], but also significantly improve enterprise performance [10] and total factor productivity [11], increase investment efficiency [12], etc. However, the digital transformation of manufacturing enterprises also faces numerous challenges and difficulties. Many companies at home and abroad are at risk of failure in their transformation. To smoothly drive enterprises to successfully achieve digital transformation and help them overcome the internal constraints of digital transformation, this paper conducts an in-depth study on the impact of managerial myopia on the digital transformation of manufacturing enterprises, which has significant practical significance.

2.2 Managerial Myopia

According to the upper echelon theory, managers' traits and cognitive patterns shape strategic choices. Managerial myopia can be classified into temporal myopia and spatial myopia in terms of dimensions. Temporal myopia reflects short-term interest orientation, while spatial myopia reflects reliance on existing technologies and markets. Both of these biases limit digital transformation strategies that require long-term investment and exploration of emerging technologies.

Managerial myopia more often specifically refers to temporal myopia. This means that managers tend to make decisions that can bring short-term profits but harm the company's long-term interests [13]. The survey report indicates that 78% of executives admit sacrificing long-term value in order to smooth out profits [14]. Managerial myopia, as a cognitive bias, often stems from managers' excessive focus on short-term performance. This focus makes them more inclined to choose projects that can bring quick returns, while neglecting strategic measures that require long-term investment and cultivation. As a result, enterprises lack a long-term perspective and strategic thinking, thereby reducing the motivation and efficiency of digital transformation. Ultimately, it will harm the future performance of the enterprise. For instance, earnings management behavior of information disclosure [14], and behavior of reducing R&D investment [15], advertising spending cuts in marketing [16] and toxic gas emissions [17].

Unlike temporal myopia, existing research on spatial myopia is extremely scarce. The earliest research on spatial myopia can be traced back to the concept of marketing myopia proposed by Levitt in 1960 [18]. Later, in theoretical research in the field of strategic management, Levinthal and March first proposed the concept of spatial myopia in their study of the myopic behavior of managers in the organizational learning process [19]. It refers to the tendency of managers to focus only on existing knowledge and technology during the learning process while neglecting the broader knowledge graph and technical domain. Existing scholars hold that if managers focus their strategic emphasis on existing technologies, fields, markets, customers and processes, this is essentially an important manifestation of spatial myopia [20, 21].

2.3 Managerial Myopia and Digital Transformation

Managerial myopia, as a cognitive bias, may affect the digital transformation process of an enterprise by influencing the strategic decisions and resource allocation of senior executives. At present, few scholars have begun to pay attention to the impact of managerial myopia on the digital transformation of enterprises, and have conducted empirical research on the impact of managerial myopia on the financial performance of digital transformation based on linear regression models [22]. Such studies have indeed proved that managerial myopia trait can have a significant and stable impact on the digital transformation of enterprises [23-25], but there are still certain deficiencies: (1) The empirical methods are monotonous. These empirical studies basically all adopt regression models. (2) The selection of variables lacks sufficient theoretical and empirical support. Various variables were chosen merely based on a brief description of the mainstream theoretical basis, resulting in the subjectification of variable selection. (3) In current research on mechanism paths, there is usually a lack of systematicness and objectivity, as well as an in-depth analysis of the objective myopic traits of managers and the digital transformation of enterprises.

With the rapid development and wide application of new-generation information technology, natural language processing technology and artificial intelligence technology, empirical analysis methods such as text mining, sentiment analysis and topic clustering are comprehensively applied to deeply analyze the direct relationship between managerial myopia and the digital transformation of manufacturing enterprises, and obtain multiple dimensions of how managerial myopia affects the digital transformation of manufacturing enterprises. It helps to make up for the deficiencies of the above-mentioned research to a certain extent. For instance, by leveraging natural language processing technology, more words related to the short-sighted traits of managers can be discovered based on word cloud. By leveraging artificial intelligence technology and based on the BERT model, the MD&A text data of the annual report is classified to discover the attitude of managers towards the digital transformation of the enterprise. Based on the LDA model, the theme distribution characteristics of managers' attention to digital transformation were discovered and verified with the short-sighted traits of managers. It was found that managerial myopia affects multiple dimensions of enterprise digital transformation, providing relatively objective research variables for subsequent related empirical studies. By means of these technologies to explore the influence mechanism of managerial myopia on the digital transformation of manufacturing enterprises is a new attempt. It can not only improve the relevant research on the digital transformation of manufacturing enterprises, managerial myopia and the application of artificial intelligence technology, but also identify the dimensions by which managerial myopia of manufacturing enterprise affects digital transformation. Furthermore, it can also unlock the "black box" of the company's internal operations, providing valuable experiences and lessons for strengthening corporate governance [26], and further offering strong support for formulating scientific and reasonable strategic decisions [27].

This paper is organized as follows: Section 3 describes research methodology, including overview of our model and experiment. Section 4 demonstrates analysis results and discussion, including word cloud, model comparative analysis, Sentiment analysis based on BERT model and LDA topic analysis. Section 5 presents conclusions.

3 RESEARCH METHODOLOGY

3.1 Overview of Our Analysis Framework

Fig. 1 shows the analysis framework of our paper based on the BERT-LDA model. The analysis process mainly includes MD&A data acquisition from annual reports, data preprocessing, technology selection and evaluation, and sentiment-topic mining based on our BERT-LDA model.

Our model integrates two key modules of improved BERT (Bidirectional Encoder Representations from Transformers) [28] and LDA (Latent Dirichlet Allocation) [29] to provide an in-depth analysis between managerial myopia and digital transformation. The improved BERT module is used to extract text semantic features of MD&A (Discussions and analyses of managers) disclosed in the annual reports of listed companies. It can synchronously record text vectors and position vectors when processing input sequences, which effectively eliminates the problem that static encoding cannot associate context and ambiguity. The LDA module is used to discover topics and identify related topic keywords in the negative sentiment orientation of MD&A.

This paper comprehensively applies the advantages of the BERT model and the LDA model. That is, the BERT model is used to classify the emotions of MD&A data, and then the LDA model is used to identify multiple key topics of negative comments, further improving the accuracy and reliability of the analysis. This combination not only leverages LDA's strength in topic recognition but also takes advantage of BERT's powerful capabilities in sentiment analysis [30], providing a more comprehensive and accurate perspective for in-depth analysis of text data.

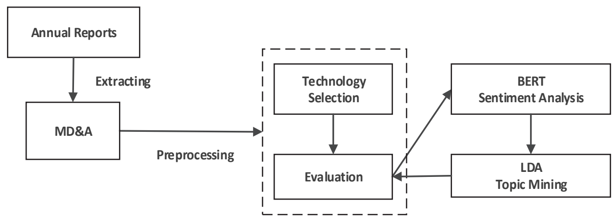

Figure 1 The analysis framework of our model

3.1.2 BERT Model

BERT (Bidirectional Encoder Representation from Transformers) model was proposed by Google in 2018 [28] and quickly attracted widespread attention in the field of NLP. The basic BERT model structure (Fig. 2) consists of an input layer, three embedding layers (Position Embeddings, Segment Embeddings, and Token Embeddings), a Transformer encoder stacking layer, and an output layer. The core innovation of this model lies in its adoption of a bidirectional Transformer architecture, which breaks the limitation of traditional language models that can only process text unidirectionally (from left to right or from right to left). By simultaneously encoding from both the forward and reverse directions of the text, it achieves in-depth mining of semantic associations in the context. This bidirectional processing mechanism enables BERT to have a more comprehensive understanding of the complexity of language context, effectively addressing the deficiencies of one-way models in semantic ambiguity handling and polysemous word understanding.

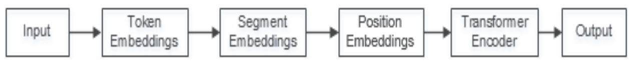

Figure 2 The structure of the basic BERT model

As a pre-trained language model based on the Transformer architecture, the core capabilities of BERT stem from large-scale unsupervised pre-training and multi-layer self-attention mechanisms. In the pre-training stage, the Model learns Language knowledge and semantic patterns in massive and diverse texts through tasks such as the Masked Language Model (MLM). Specifically, the MLM task masks some words in the text, prompting the model to predict the masked words based on the context. This process enables it to deeply grasp the semantic dependencies between words. The multi-layer self-attention mechanism enables the model to flexibly focus on words at different positions in the text, accurately capture long-distance semantic associations, and provide rich feature representations for subsequent tasks.

The advantages of the BERT model and its variations in natural language processing have been verified many times. In this study, we use the "Chinese-MacBERT-Base" model as the initial encoder, and then conduct parameter tuning and model optimization based on the results of multiple experiments. The model of this study adopts the same 12-layer bidirectional Transformer architecture as BERT-Base, with a hidden layer dimension of 768 and a Multi-head Attention head of 12. The total reference quantity is approximately 102M. To enhance the performance of downstream tasks, the model introduces an MLM error correction (Mac) mechanism during the pre-training stage, further improving the robustness of mask language modeling.

After loading the model, we do not freeze the underlying parameters. We adopt a hierarchical learning rate (encoder $1e^{-5}$, classification layer $3e^{-5}$), obtain a 2304-dimensional sentence vector through the concatenation of the triple representation of "[CLS] + Mean pooling + Max pooling", and then connect to a randomly initialized fully connected layer to complete the three-classification. During the training phase, we use the function of cross-entropy loss to compute the loss value, combined with category balance weights and cosine annealing learning rate scheduling, to achieve the best macroscopic F1 within 10 epochs. Finally, a soft voting integration was conducted on the models under the three random seeds to obtain more stable prediction results. The specific algorithm is as follows:

Algorithm 1: MacBERT - Multi-scale Pooling -Integrated Training process
Input: dataset (text X, label Y), pre-trained MacBERT model, hyperparameters (learning rate: $1e^{-5}$ for BERT layer / $3e^{-5}$ for classification layer), random seed list, mixed-precision training switch
Initialization: Load the weights of the pre-trained MacBERT model, and randomly initialize the linear classification layer
for each random seed *seed* $\in$ *RANDOM_SEED_LIST* ***do***
Data preprocessing: Label mapping ($-1 \rightarrow 0$, $0 \rightarrow 2$, $1 \rightarrow 1$), dividing the training/test datasets in an 8:2 ratio, and constructing the data loader after tokenizing the text
Model configuration: Instantiate the model and migrate it to the GPU, configure AdamW (Hierarchical Learning Rate), CosineAnnealingLR scheduler, and initialize the mixed-precision scale (if enabled) ***for*** epoch $\leftarrow 1$ ***to*** N_{epochs} ***do***
Model training: The model switches to the training mode
for each batch of data ***batch*** $\in$ ***train_loader do***
Clear the gradient and move the input data and labels to the GPU
Forward propagation:
bert_output $\leftarrow$ *MacBERT(input_ids,attention_mask)*
cls_vec $\leftarrow$ *bert_output[:,0] (cls token)*
mean_vec $\leftarrow$ *mean(bert_output,dim=1)*
max_vec $\leftarrow$ *max(bert_output,dim=1)*
concat_vec $\leftarrow$ *concat([cls_vec,mean_vec,max_vec],dim=−1)*
logits $\leftarrow$ *Linear(concat_vec)*
Calculate the loss: *L CrossEntropyLoss (logits,labels,weight=class_weights)*
Backpropagation: (including mixed precision processing), gradient clipping (norm 1.0), update parameters and learning rate
end
Model verification: Calculate the weighted F1 of the test datasets and save the current optimal model
end
Integrated reasoning: The best model for loading all seeds
for each batch of data ***batch*** $\in$ ***test_loader do***
Each model independently propagates forward to calculate the category probability $\rightarrow$ take the mean (soft voting) $\rightarrow$ select the category with the highest probability as the prediction
end
Evaluation: Accuracy $\leftarrow$ ***Accuracy, Recall rate*** $\leftarrow$ ***Recall, F1*** $\leftarrow$ ***F1_score, AUC*** $\leftarrow$ ***AUC***
Output: The trained integrated model and various evaluation metrics

In the operation process of this model, we carry out targeted data preprocessing first. Considering that the MD&A text contains a large number of industry terms, financial statements and strategic planning content, it is necessary to first label the professional terms and clean the redundant information of the text, and then convert the text into a vector form that meets the input requirements of the BERT model through splitting words, removing stopwords, and format standardization processing. Subsequently, we input these preprocessed text data into the BERT model. By leveraging its bidirectional Transformer architecture and multi-layer self-attention mechanism, we deeply capture the contextual semantic associations of words in the text and extract the high-dimensional semantic features that integrate the self-meanings of the words with contextual information. Finally, we finish sentiment classification and output three types of sentiment results, namely "positive" (1), "negative" (–1), and "neutral" (0).

In this study, the BERT model is chosen to handle the MD&A text sentiment classification mask mainly based on the following significant practical significance and adaptability: Firstly, as the core carries for managers to convey corporate strategies and business conditions, the sentiment tendencies of MD&A text data are often hidden in complex contexts and professional expressions. The bidirectional semantic coding ability of BERT can accurately extract these implicit information, avoiding emotional misjudgments caused by imcomplete understanding of the context. Secondly, MD&A text data of manufacturing enterprises involve a large number of industry terms, financial data and strategic planning contents. The language style of MD&A text data is formal and highly professional. The strong generalization ability, formed by large-scale multi-domain text pre-training, enables BERT to quickly adapt to such special texts and efficiently understand the semantic features of the texts. Finally, during feature extraction, BERT maps each word to a high-dimensional vector space that integrates context information. These feature vectors, which contain rich semantic information, can provide strong support for the precise classification of managers' three types of attitudes ("positive", "negative", and "neutral") and ensure the reliability of emotional labels. This will further lay a solid foundation for the subsequent in-depth analysis of managerial myopia.

3.1.3 LDA Model

LDA (Latent Dirichlet Allocation) is a document topic generation model, also known as a three-layer Bayesian probability model, which contains a three-layer structure of words, topics and documents. This model was first proposed by David Blei et al. in 2003 [29] and is a text mining tool based on machine learning and natural language processing. This model regards each document as a mixture composed of multiple different topics, and each topic is made up of several related words. The core task of LDA is to infer the implicit topic distribution in the document and the word distribution under each topic, and to infer the topic of the article by analyzing the multiple topic distribution probabilities of each document. The LDA blueprint and calculation formula are shown in Fig. 3 and Eq. (1).

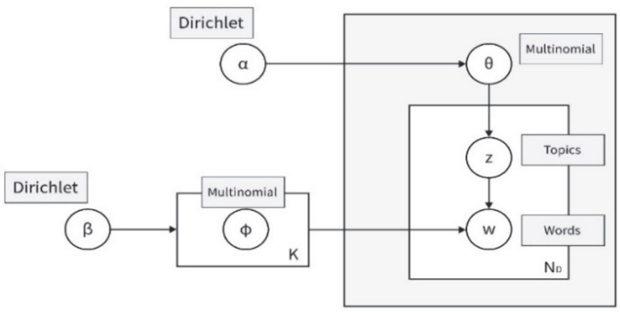

Figure 3 LDA blueprint

$$P\left(W,Z,\theta,\varphi;\alpha,\beta\right)=\prod_{j=1}^{M}P\left(\theta_j;\alpha\right)\prod_{i=1}^{K}P\left(\varphi_i;\beta\right)\prod_{t=1}^{N}P\left(Z_{j,t}|\theta_j\right)P(W_{j,t}\mid\varphi Z_{j,t}) \tag{1}$$

Here, α represents the Dirichlet prior parameters of the document-topic distribution, β is the Dirichlet prior parameters of the topic-word distribution, θ is the topic multinomic distribution parameter of the document, φ is the polynomial distribution parameter of the topic word, z is the topic corresponding to the N-th word of the D-th document (hidden variable), and w is the observed word of the N-th word of the D-th document.

Based on the BERT sentiment classification, we introduce the LDA topic model to construct a secondary analysis framework. Our aim is to conduct in-depth topic mining on the negative comments of managers identified by BERT and systematically sort out the core influencing factors that lead to managerial myopic behavior in the digital transformation of manufacturing enterprises. Through unsupervised learning, we extract explanatory topic structures from unstructured negative texts, effectively compensate the limitation of sentiment classification that can only determine attitude tendencies but cannot reveal deep-seated reasons. It provides a quantitative analysis tool for analyzing the specific manifestation dimensions of managerial myopia traits.

In this study, the implementation process of LDA topic clustering consists of three key steps: Firstly, we carry out targeted preprocessing on the negative comments output by BERT, including removing meaningless words and stopwords. After the data preprocessing, we build domain-specific dictionaries and form a corpus suitable for LDA analysis. Secondly, we determine the optimal number of topics K (K = 6) through confusion calculation and topic consistency test. We use the LDA model to model the topics of the preprocessed text, generate the document-topic probability distribution and the topic-vocabulary probability distribution. Finally, we name and explain each topic based on the distribution of keywords and the actual text contents, and then summarize the main manifestation dimensions of managerial myopia behavior.

For the negative comments identified by BERT, we choose the LDA model for topic clustering, which has a clear research purpose and adaptability. Firstly, in the negative evaluations of digital transformation by managers, there are often multiple factors that lead to their short-sighted behavior. These factors are interwoven and require an effective approach to sort out and summarize. The topic clustering capability of LDA can aggregate these scattered expressions into logically related topic dimensions. Secondly, MD&A text data of manufacturing enterprises contain a large number of industry-specific terms and strategic statements. LDA model can void the possible biases caused by researchers' subjective presuppositions of short-sighted dimensions. The excavated topics are all directly derived from the text data itself. It makes the research conclusions have a stronger empirical basis. This analytical path from textual evidence to theoretical construction has effectively enhanced the scientificity and persuasiveness of the research on the managerial myopia traits.

3.2 Experiment

Step 1: Data Acquisition

The MD&A in the annual report data of listed companies is an important window reflecting the managers' understanding of the company's strategic planning. Therefore, when exploring the impact of managerial myopia on the digital transformation of enterprises, this paper first collected a total of 4816 valid annual report data from 415 Chinese intelligent manufacturing enterprises over the past decade, and then extracted MD&A text data from them to obtain detailed information on managers' behavior and the digital transformation of manufacturing enterprises.

Step 2: Data Preprocessing

(1) Data cleaning. The original MD&A text data contains some invalid data, such as special symbols, year, month and day, and meaningless website information, etc. These invalid data and information will affect the subsequent text analysis results. Therefore, this paper needs to clean these original comment texts. After the above cleaning, a total of 4816 valid MD&A data were obtained, and the data was saved locally in the form of an Excel table.

(2) Splitting words. This paper uses Jieba word segmentation tool in Python to perform word segmentation on comment text. Jieba word segmentation is an open-source Chinese word segmentation tool that can segment a piece of Chinese text according to the granularity of words and tag each word with a part-of-speech label. Jieba word Segmentation employs a word segmentation algorithm based on prefix dictionaries and suffix rules, featuring high accuracy and speed in word segmentation. It is widely applied in fields such as natural language processing, search engines, and information retrieval. Although the default word segmentation library of Jieba word segmentation is already very comprehensive, some specific field or industry terms may not be included in the default word segmentation library. In such cases, custom dictionaries can be added to make up for the deficiency. The obtained annual report comment text contains many proper nouns that have nothing to do with the comments and attitudes of managers. Therefore, this paper constructs a custom dictionary and uses regular expressions to count the word frequency, filtering out irrelevant words such as "de", "le", "in", and "often" that frequently appear in the text but have little impact on the meaning of the text. By calling the jieba.load_userdict() method to load a custom dictionary, the accuracy of word segmentation can be improved, making the data analysis results closer to the real ones.

(3) Removing stopwords. Stop words refer to some common, meaningless or useless words. These words are of no help to the results of text analysis; instead, they may interfere with the subsequent processing of the text and affect the accuracy of the analysis results. This paper uses the stop word list of Harbin Institute of Technology to remove stop words and optimize the Jieba word segmentation results, facilitating subsequent data mining analysis.

Step 3: Word Cloud Analysis

Word cloud is an intuitive graphical representation of text data visualization. By presenting the key words in the text in fonts of different sizes and colors, it can visually reflect the frequency and importance of the key words in the text. High-frequency words are displayed in larger fonts and more eye-catching colors, while low-frequency words are presented in smaller fonts, forming a "cloud" layout.

The core function of the word cloud is to visually and intuitively reflect the distribution of key words in the text through comparison. Therefore, this paper can initially explore the key words in the MD&A text data with the help of word cloud graph, and visually display the frequently occurring words in the MD&A text data. After completing word segmentation and stop word filtering, in order to visually present the distribution characteristics of core words in the text, this paper converts the word frequency of each segmented word into corresponding weight data (the weight is positively correlated with the word frequency, that is, the higher the word frequency, the greater the weight), and uses the matplotlib library of Python for canvas Settings and parameter adjustments. Generate a visual word cloud in combination with the WordCloud library. Among them, matplotlib is an open-source Python plotting library that supports the drawing of various types of charts and is widely used in fields such as data visualization and scientific computing plotting. WordCloud, on the other hand, is a Python library dedicated to word cloud generation. It can automatically adjust the display size and weight of words in the word cloud based on their occurrence frequency, and is often used for the intuitive display of text content, helping researchers quickly identify key information in the text. The font size of the words in the word cloud is determined by their corresponding weights. The higher the weight, the larger the font. This clearly shows the high-frequency core words and their relative importance in the manager's comment text, providing an intuitive preliminary reference for subsequent topic extraction and sentiment analysis.

Step 4: Model Training and Evaluation

In the study of the impact of managerial myopia on the digital transformation of enterprises, by analyzing the emotional tendencies in managers' comments, one can gain insights into their attitudes and levels of support for digital transformation. Positive emotions can indicate support for digital transformation, neutral emotions do not reflect an attitude towards digital transformation, and negative emotions may imply myopia or resistance. In the section on sentiment classification, two independent annotators selected 1664 pieces (approximately 35%) of sample data for manual annotation and marked the sentiment tendencies (–1 indicates negative, 0 indicates neutral, and 1 indicates positive). To balance the three emotional tendencies in the dataset, we selected 1050 pieces of data from 1664 manually labeled pieces of data in a 1:1:1 ratio for the subsequent construction of sentiment classification model. Meanwhile, to measure the consistency degree of the two independent annotators on this sentiment classification, we calculated Cohen's Kappa coefficient, which is approximately 0.86, indicating that the two independent annotators have a strong consistency in the annotation of the sentiment classification.

To enhance the diversity and scale of the data, we use EDA (Data Augmentation Technology) to preprocess the extracted 4816 MD&A text data. EDA generates diverse training samples through methods such as synonym replacement and random insertion, enhancing the model's adaptability to different expression methods and thereby improving the model's generalization ability. In terms of the sentiment classification of managers towards digital transformation, we train multiple machine learning and deep learning classification models, including Random Forest, Bayes, CNN, RNN, BiLSTM, Word2Vec + SVM and BERT. By comparing and evaluating the classification performance of these models through metrics such as accuracy rate, recall rate, F1 score and AUC, we can determine the optimal model suitable for this dataset. Finally, we apply this optimal model to complete the sentiment classification of MD&A text data.

During the model training process, we first divide all text datasets into training datasets and test datasets in a 8:2 ratio, and then adopt appropriate parameter settings for different models. For example, we set the following parameters:

Random Forest model parameter settings: random seed random_state = 42; stratify = y; joint parameter tuning with RandomForestClassifier under the GridSearchCV framework.

Bayes model parameter settings: max_df = 0.8; min_df = 3; alpha = 1.0; fit_prior = True.

CNN model parameter settings: adopt a lightweight architecture of two-layer Conv1D stacking; output dimension of the Embedding layer: 128; the first layer of Conv1D: 128 5-gram convolution kernels, connected to 2-stride MaxPooling; the second layer of Conv1D: 64 3-gram convolution kernels, connected to GlobalMaxPooling. The entire process uses l2 (0.001) weight attenuation. Reduce LROnPlateau (patience = 3, factor = 0.2, min_lr = $1e^{-4}$) is jointly scheduled with EarlyStopping (patience = 5, restore_best_weights); batch size: 64.

RNN model parameter settings: adopt a dual-channel BiSimpleRNN architecture. The main channel input: 2000-word × 64-dimensional; three layers of bidirectional Bisimplernn (64-64-32 hidden units, 0.3 dropout + 0.3 recurrent dropout); l2 = $1e^{-5}$) to extract sequence features; Adam lr = $1e^{-3}$, clipnorm = 1.0.

BiLSTM model parameter settings: adopt a 3-layer residual bidirectional LSTM (BiLSTM) as the backbone; hidden dimension of 256×2 (bidirectional 512); input embedding: 300 dimensions; upper limit of the vocabulary of 80 k; a fixed-length sequence of 64 tokens; Dropout: 0.3; Class-Balanced Focal Loss ($\beta = 0.9999$, $\gamma = 2$); AdamW (lr = $1e^{-3}$, weight_decay = $1e^{-4}$); CosineAnnealingWarm Restarts ($T_0 = 5$, T_mult = 2); batch_size: 64.

Word2Vec + SVM model parameter settings: Word2Vec model parameter Settings: vector_size = 300, min_count = 5, window = 5, sg = 0 (CBOW), hs = 0; alpha = 0.03; epochs = 20. SVM model parameter Settings: C = 10, gamma = 0.1.

BERT model parameter settings: select the "Chinese-MacBERT-Base" model as the initial encoder; vocabulary size 21,128; the maximum number of supported positions 512; embedding dimension 768; the number of Transformer layers 12; the number of multi-head self-attention mechanism heads 12; the total number of references approximately 102M, and the learning rate of the adopted AdamW optimizer: 10^{-5} for BERT layer/3×10^{-5} for classification layer; CosineAnnealingLR scheduled to $1e^{-6}$.

This parameter configuration ensures the sufficiency of training data while retaining a sufficiently large test set for evaluating the model's generalization ability. After optimization, the robustness and generalization performance of the model has been significantly improved. We take Accuracy rate, F1 score, Recall rate, and AUC as the core evaluation indicators for model selection. By comparing the classification results of various models, the optimal model is determined and applied to the sentiment classification task of digital transformation of MD&A text data. While ensuring sufficient training data, sufficient test data is retained to evaluate the generalization ability. After optimization, the robustness and generalization ability of the model has been significantly improved.

After completing the sentiment classification of digital transformation in manufacturing enterprises, we explore the relationship between managerial myopia and digital transformation based on the LDA model. In this section, all negative comments on digital transformation in MD&A text data need to be extracted. The LDA model is used to conduct topic analysis on these negative comments to identify the topics and related keywords.

4 RESULTS AND DISCUSSION

4.1 Word Cloud

After data preprocessing, the final generated word cloud is shown in Fig. 4. Through the generated word cloud, we can intuitively understand the keywords that managers care about, such as "product", "project", "funds", "invest", etc. These keywords reflect the focus of managers on matters related to the digital transformation of manufacturing enterprises. For example, the high-frequency keywords of "project", "funds" and "invest" indicate that managers pay attention to the advancement of digital transformation projects, the allocation of financial resources and the implementation of the transformation. The prominences of "product", "technology", "develop" and "market" may reflect that managers focus on how digital transformation can empower product optimization, technological development and market situation of enterprises.

Figure 4 Word cloud

In addition, some keywords reflecting the managerial myopia have also been identified. The keywords related to "myopic perspective" in the MD&A text data include both direct and indirect categories. The direct categories include "during the period", "this issue", "last year" and "year-on-year". The indirect category includes two subcategories: temporal myopia and spatial myopia. For example, some keywords likes "project", "funds", "invest", "sales", "trade" and "income" can serve as potential temporal myopia signals. They may reflect that managers place more emphasis on current financial performance and pay insufficient attention to the long-term value of digital transformation (such as technological iteration and the accumulation of model innovation). Some Keywords like "product", "production", "technology", and "market" can serve as potential spatial myopia signals. They may reflect that managers focus their strategic emphasis on existing technologies, production, markets.

4.2 Model Comparative Analysis

Through the training of models such as Random Forest, Bayes, CNN, RNN, BiLSTM, Word2Vec+SVM and BERT, the results of Accuracy, F1, Recall, and AUC of each training model are shown in Tab. 1.

To present the performance comparisons more clearly, we further visualize the comparison results of the above four indicators of each model. The performance comparison results of the models are shown in Fig. 5.

Table 1 Training results of different models

Model	Accuracy	F1	Recall	AUC
Random Forest	0.77	0.77	0.77	0.90
Bayes	0.83	0.83	0.83	0.90
CNN	0.82	0.82	0.82	0.94
RNN	0.81	0.65	0.81	0.83
BiLSTM	0.67	0.53	0.67	0.50
Word2Vec+SVM	0.81	0.80	0.80	0.90
BERT	0.91	0.90	0.90	0.98

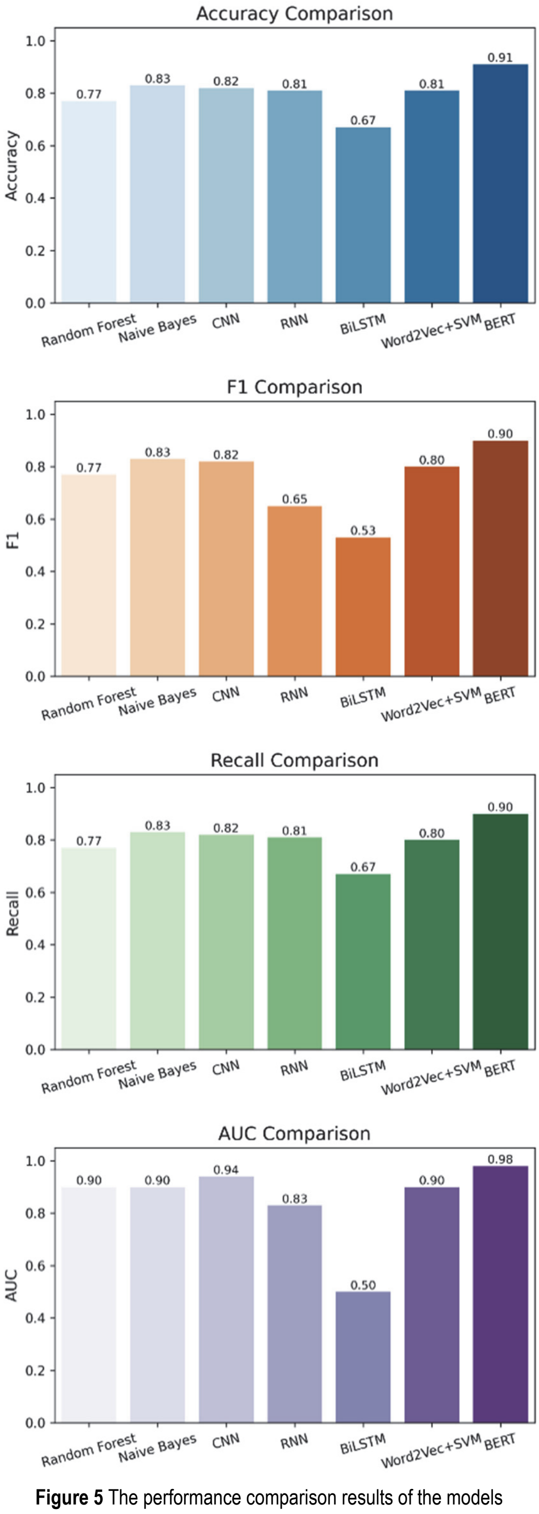

Figure 5 The performance comparison results of the models

The final performance comparison results show that the BERT model performed the best among all the models. By classifying the emotions of managers' comments through the BERT model, we can accurately identify managers' attitudes and levels of support for digital transformation. The BERT model performs well in various natural language processing tasks, and its pre-trained deep bidirectional representation can capture rich semantic information in the text [28]. This ability enables the BERT model to have a high accuracy rate in sentiment classification tasks and can provide a reliable sentiment label basis for subsequent topic clustering analysis. Therefore, we adopt the BERT model to conduct sentiment classification on 4816 MD&A text data and further analyze the impact of managerial myopia on the digital transformation of enterprises.

The sentiment classification results of digital transformation of manufacturing enterprises based on the BERT model show that: Managers have inconsistent attitudes towards the digital transformation of manufacturing enterprises. Among them, there are 1262 positive comments, 1015 negative comments, and 2539 neutral comments. That is, the proportion of positive emotions is approximately 26%, negative emotions is approximately 21%, and neutral emotions is approximately 53%. From the statistical results, it can be seen that, over the past decade, the attitude of many enterprise managers towards digital transformation remains unclear. Furthermore, nearly one fifth of enterprise managers still have a negative attitude towards digital transformation. It reflects that some senior executives have myopic cognition or resistance in the process of promoting digital transformation.

4.3 Sentiment Analysis Based on BERT Model

The research purpose of this paper is to explore the relationship between managerial myopia and digital transformation. Therefore, in the LDA topic analysis, we only analyzes the negative comments of managers. In the next section, we use the LDA model to conduct topic analysis on negative comments and identify the topics and related keywords in the MD&A text data.

4.4 LDA Topic Analysis

To further explore the relationship between managerial myopia and digital transformation, we use LDA to mine the distribution of potential information topics in negative comment data. When conducting LDA topic word analysis on negative comments related to the myopia of senior executives, we need to first extract all the negative comments from 4816 MD&A text data, and then pre-set the number of topics n_topics. After repeated experiments and perplexity analysis, it is found that when the number of topics was 6, the quality of the topics output by the LDA model is the best. Therefore, we select six topics and ultimately choose the top 10 keywords. The topics and related keywords are shown in Tab. 2.

From the negative comment topic keywords extracted from the topic model, it can be seen that the terms related to "myopic perspective" disclosed in MD&A text data can effectively reflect the inherent myopic traits of managers, such as "product", "investment", "project", "amount", "income", etc. Moreover, these terms related to "myopic perspective" frequently appear in negative comments on digital transformation, indicating a significant connection between managerial myopia and negative comments on digital transformation. Furthermore, the repeated appearance of company names such as Chenming and Wuliangye, etc. indicates that management short-sightedness is particularly evident in traditional industries (such as papermaking, liquor, and fertilizers), which still rely heavily on traditional business models. This indicates that spatial myopia is more common in industries with strong path dependence.

Table 2 LDA topic analysis

Topic	Keywords
Topic #0	Product Operating Investment COFCO R&D Activity Amount Cost Cast Pipe Income
Topic #1	Wuliangye Yihua Investment Fertilizer Mining Woolen Textile Fusion Business Improvement Subsidy Funds
Topic #2	Product Operating Investment Activity Amount R&D period Project Operating Income
Topic #3	Chenming Yunnan Baiyao Project Investment Fertilizer Products papermaking Conference Audit Capsules
Topic #4	Product project Business investment R&D development Market operation Increase revenue
Topic #5	Product Derivatives Investment Business Project Cash Shaogang FAW Reduction Amount

The negative comment topics extracted from the topic model show that the myopic negative performance of senior executives in the digital transformation process of manufacturing enterprises presents multi-dimensional characteristics. It is closely related to the core links of digital transformation.

Topic #0 focuses on the imbalance between short-term business operations and R&D investment. High-frequency terms such as "operating", "revenue", and "cost" reflect executives' excessive focus on current business performance, while the low-frequency association of "R&D" implies neglect of the technological research and development required for digital transformation - this is contrary to the core requirement of "technology-driven innovation" in digital transformation. It reflects the myopic tendency of senior executives between short-term performance and long-term technological accumulation.

Topic #1 centers on the reliance on traditional business and insufficient investment in transformation. The strong association between traditional industry terms such as "fertilizer", "mining", and "woolen textile" and "investment" and "operation" indicates that executives are still confined to their existing business areas and have insufficient investment in emerging technologies or cross-industry layouts required for digital transformation, reflecting the limitations of spatial myopia on the perspective of transformation.

Topic #2 highlights the suppression of long-term projects by short-term performance orientation. Terms like "within the period" and "amount" directly point to the focus on current financial indicators, while the relatively low frequency of "research and development" and "projects" indicates that executives may reduce investment in digital transformation projects to achieve short-term goals, presenting a myopic feature of "emphasizing the present over the long term".

Topic #3 involves the disconnection between specific project management and system transformation. The association between company names such as "Chenming" and "Yunnan Baiyao" and "projects" and "audits" reflects that senior executives overly focus on the short-term benefits of individual projects while neglecting the systematic layout required for digital transformation, demonstrating a myopic understanding of the overall nature of the transformation.

Topic #4 reflects the disconnection between the current market reliance and long-term development. The frequent aggregation of "product", "market", and "operation" indicates that executives focus on the market performance of existing products, while the weak correlation between "development" and "research and development" implies the neglect of long-term values such as "new market expansion" and "technological iteration leading new demands" in digital transformation. Present the limitations of spatial myopia on market vision;

Topic #5 points to the conflict between short-term cash flow management and transformation investment. Words such as "cash", "reduction", and "amount" reflect the excessive sensitivity of executives to short-term cash flow. They may maintain the stability of current cash flow by cutting the long-term investment required for digital transformation, which contradicts the "high investment, long return" characteristics of transformation.

As shown above, the thematic analysis results of the LDA model indicate that the negative impact of executive myopia on the digital transformation of manufacturing enterprises can be summarized into six dimensions: Short-term performance orientation suppresses R&D investment, traditional business reliance restricts the vision of transformation, current indicators focus squeezes long-term projects, specific project management neglects systematic transformation, existing market reliance weakens long-term planning, and short-term cash flow control reduces transformation investment. These dimensions collectively constitute the resistance to digital transformation. Managerial myopia in time leads to a tilt of resources towards short-term goals, while Managerial myopia in space restricts the cross-border exploration and systematic layout required for transformation. If manufacturing enterprises want to break through the bottleneck of transformation, they need to guide senior executives to escape the above-mentioned myopic traps and promote the implementation of digital strategies with the thinking of "prioritizing long-term value and emphasizing systematic layout".

5 CONCLUSIONS

The "myopic perspective" language disclosed by managers in the annual report reflects the characteristics of their cognition of time and space, and this inherent trait will influence the decision-making behavior of managers. Based on the upper echelons theory of social psychology, this paper takes the content of the management Discussion and Analysis in the annual reports of listed manufacturing enterprises in China as the object, and empirically examines the impact of managerial myopia on the digital transformation of manufacturing enterprises by using the BERT-LDA model.

The research results show that: (1) The more "myopic perspective" terms are disclosed by MD&A text data, the more it reflects that the manager has the orientation traits of temporal and spatial myopia. The research results provide evidence support for the appointment of high-level management talents in enterprises, that is, when enterprises select and cultivate senior managers, they should not only pay attention to their demographic characteristics, but also focus on the traits of managers' cognition of time and space. (2) The impact of managerial myopia on the digital transformation of manufacturing enterprises can be summarized into six dimensions: short-term performance orientation suppresses R&D investment, traditional business reliance limits the vision of transformation, current indicator focus squeezes long-term projects, specific project management neglects system transformation, existing market reliance weakens long-term planning, and short-term cash flow control reduces transformation investment. These dimensions collectively constitute the resistance to digital transformation: temporal myopia leads to a tilt of resources towards short-term goals, while space myopia restricts the cross-border exploration and systematic layout required for transformation. For practitioners, these six definite dimensions provide a diagnostic framework. Enterprises can alleviate time shortsightedness by redesigning executive incentive mechanisms to reward long-term innovation achievements, and reduce space shortsightedness by encouraging cross-industry cooperation and R&D partnerships. Decision-makers can also require listed companies to disclose not only financial indicators but also forward-looking innovation investments in MD&A reports, thereby curbing excessive short-termism. If manufacturing enterprises want to break through the bottleneck of transformation, they need to guide senior executives to escape the above-mentioned short-sighted traps and promote the implementation of digital strategies with the thinking of "prioritizing long-term value and emphasizing systematic layout".

If manufacturing enterprises want to break through the bottleneck of transformation, they need to guide senior executives to escape the above-mentioned myopic traps and promote the implementation of digital strategies with the thinking of "prioritizing long-term value and emphasizing systematic layout".

The shortcomings of this paper lie in the following aspects: First, in the data collection and analysis of the MD&A for the annual reports of manufacturing enterprises, it is aimed at the entire manufacturing enterprise and does not specifically study a certain type of manufacturing enterprise. Secondly, although this paper empirically analyzed the relationship between managerial myopia and digital transformation based on the BERT-LDA model, it is necessary to further confirm the extent to which managerial myopia affects digital transformation. Third, this study is limited by its reliance on a manually labeled subset of MD&A text data and potential subjectivity in interpreting LDA topics. Moreover, results are based solely on Chinese manufacturing firms, which may limit generalizability. Future research could expand the dataset cross-nationally, adopt larger-scale annotation with crowdsourcing, and compare BERT-LDA with other emerging topic models. Furthermore, future research could conduct an empirical study on a specific type of manufacturing enterprise to explore the extent to which managerial myopia affects the digital transformation of manufacturing enterprises, and thereby improve the corporate governance mechanism to help manufacturing enterprises develop sustainably and healthily.

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Contact information:

Feng HU
School of Management,
Guangdong University of Technology,
161 Yinglong Road, Tianhe District, Guangzhou 510520, China
E-mail: fenghu@gdut.edu.cn

Jianchao LIU
School of Management,
Guangdong University of Technology,
161 Yinglong Road, Tianhe District, Guangzhou 510520, China
E-mail: 2068498187@qq.com

Yingtong CHEN
(Corresponding author)
School of Management,
Guangdong University of Technology,
161 Yinglong Road, Tianhe District, Guangzhou 510520, China
E-mail: c2395484662@163.com