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A Study of the Role of Generative AI Academic Writing Assistants in Enhancing the Efficiency of Academic Research in Business Studies

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SUMMARY: *Although the current generative AI academic writing assistant has deeply penetrated the literature retrieval and data analysis of business academic research, whether it can effectively improve the efficiency of business academic research remains to be verified. In this paper, the generative AI academic writing assistant based on business academic research is divided into two modules, information extraction and writing output, to form a business academic writing assistant model. The model proposes a Bert-based extractive summarization method in the extraction of key information of academic text, adopts BertSum to extract the feature vectors of academic text, uses BiGRU to capture the contextual relationship between sentences, integrates GRTU encoder and attention mechanism to accurately extract the relevant information, and utilizes the classification layer to judge whether the sentence stays or goes. In terms of academic text writing output, a selector is utilized to filter out important academic text arguments, and a rewriter is used to generate the corresponding complete academic research content. Logistic regression model was chosen as the research analysis tool, research samples were selected, business academic research efficiency was set as the dependent variable, and the prediction model was constructed based on the results of regression analysis parameter estimation of the seven independent variables. The prediction model of business academic research efficiency predicted 236 students with more than 80.00% accuracy for all three academic research efficiencies.*

KEYWORDS: *business academics; generative AI academic writing; logistic regression; academic research efficiency*

1 Introduction

In the era of rapid development of intelligent information technology, generative artificial intelligence (AIGC) is gradually penetrating into various fields, from commercial advertisement to medical diagnosis to academic research, the application of AIGC is becoming more and more widespread [1]. Especially in the fields of education and research, AIGC shows great potential. As the force of scientific research and innovation, the cultivation of postgraduate students' scientific innovation is crucial to the development of the whole science and technology and social progress. As the scale of China's postgraduate education continues to expand, how to improve postgraduates' scientific research innovativeness has become a focus of attention for universities and research institutions [2-4]. In this context, the introduction of AIGC provides graduate students with a new way of research production. However, with the wide application of AIGC, there are two different views on the impact of AIGC on graduate students' research innovativeness: “technology empowerment” and “tool

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dependence" [5]. In the view of "technology empowerment", AIGC is regarded as an important means to improve research efficiency and innovation ability. By providing convenient literature review, automated data analysis and intelligent research assistance, AIGC can help researchers better carry out scientific research and stimulate innovative thinking [6, 7]. Those who hold the view of "tool dependence" believe that over-reliance on AIGC may lead to a lack of autonomy and creativity in the research process, and may even affect the overall development of research ability [8, 9].

AIGC represented by ChatGPT and DeepSeek integrates processes such as "perception", "retrieval", "interaction", and "generation" in knowledge behavior, providing researchers with an efficient way to acquire knowledge and helping them extract valuable information from massive amounts of data [10, 11]. And analyzing and solving scientific problems from different perspectives and levels, and generating new knowledge from existing knowledge, which makes more and more researchers change from the traditional search behavior knowledge acquisition to the use of AI-assisted knowledge acquisition [12]. This transmutation process of knowledge acquisition behavior and its inducing factors is an issue worth exploring, which is of great theoretical and practical significance for improving the knowledge acquisition ability and knowledge literacy level of researchers.

Generative Artificial Intelligence (GAI) has been favored by many researchers due to its excellent task processing ability and responsiveness [13]. Researchers are trying to apply GAI in scientific research to assist scientific research, solve scientific research problems, handle scientific research tasks, and improve scientific research efficiency. At present, scholars' research on GAI and scientific research applications mainly focuses on four aspects: scientific research scenarios of GAI applications, new paradigm of GAI-driven research, comparison of GAI-enabled scientific research, and AI literacy of researchers [14-16]. In terms of scientific research scenarios of GAI application, literature [17] explored the impact of GAI on various stages of academic research, including creative conceptualization, literature review, data analysis, etc., and found that GAI can change academic research design, data collection, data analysis, and academic writing, improve academic research efficiency, and promote innovation. Literature [18] provides an operational guide for the use of large-scale language models such as ChatGPT in academic environments, focusing on GAI's ability to enhance the efficiency of scientific research through intelligence, diversity, and collaboration, but also the need to consider ethical issues and limitations. In the interview data from the literature [19], it was pointed out that GAI tools, represented by ChatGPT, have changed the way scientific data is processed, as well as the traditional way of reading it, and in a way, have improved the researchers' ability to conduct research.

In terms of the new paradigm of GAI-driven research, literature [20] suggests that GAI technology can be used as a personal English tutor to help non-native English-speaking research entrants to write in English, which lowers the threshold of writing in English, and allows them to spend more energy on the content of their research. Literature [21] points out that GAI technology can be seen as an aid to creative, and critical academic writing, but also has problems with academic misconduct, plagiarism attribution and legality. Literature [22] proposed a new research paradigm for economic and financial research using GAI, covering research objectives, scientific data, and modeling; this new paradigm explores the impact and perspectives of GAI in academic research in the field of economics and finance, covering five scenarios, including portfolio management, economic and financial forecasting, extreme scenario analysis, policy analysis, and financial fraud detection. Literature [23] suggests that GAl is leading a new paradigm in academic research, which is able to shift from a task-specific model, to a universal application model that facilitates the design and development of research through reverse design, data augmentation, and solving complex mathematical modeling.

In terms of the comparison of GAI-enabled research, literature [24] provides insights into the dilemmas and trade-offs involved in behavioral big data knowledge acquisition and analysis in the process of conducting causal behavioral research by researchers, aiming to address the scientific, technological, and ethical challenges faced by researchers in applying behavioral big data. Literature [25] explored the relationship between information retrieval behavior and prior knowledge among graduate students at the University of Tehran, and the results showed a positive correlation between the two, as well as a positive and important relationship between some of the dimensions of information seeking and prior expertise, familiarity, and experience. Literature [26] investigated whether ChatGPT, an application of GAI technology, can help researchers to write abstracts, and the results showed that the abstracts generated by ChatGPT had no obvious errors and conformed to the abstract writing specifications, which can be a powerful tool for scientific writing in the future.

In terms of AI literacy among researchers, literature [27] proposes an AI literacy enhancement framework, namely, the Artificial Intelligence Academic Application Framework (AIAP), which can significantly improve researchers' confidence in using GAI by teaching them relevant basic concepts and vocabulary, how Generative Artificial Intelligence (GAI) works, and how to construct effective cues to enhance researchers' AI literacy. Literature [28] developed a comprehensive assessment framework for the AI literacy development process, aiming to provide researchers with an assessment pathway using multiple methods (including quasi-experimentation and methodological cross-validation) to improve researchers' academic efficiency. Using five AI literacy frameworks, literature [29] critically analyzes and discusses the relationship between the components of AI literacy and technological literacy, focusing on techno-scientific knowledge and socio-ethical-technical understanding of researchers, with less emphasis on AI skills.

This paper firstly outlines the key technical means of Bert-based extractive summarization method, parsing the Bert vector representation layer, the above text feature extraction layer, the context-enhanced attention layer and the key sentence summarization layer in order. It also discusses the operation principles and steps of content selector and text rewriter in academic writing generation, and builds a writing assistant model based on business academics. Then we evaluate the operation effect of the business academic writing assistant model from the two levels of language use effect and text generation effect. Logistic regression model was then used as the research analysis method to select the research samples, collect and organize the research data through interviews and questionnaires, and complete the research preparation. The dependent and independent variables were selected, the basic contents of the research variables were listed and the variable data of the samples were counted. Finally, based on the results of parameter estimation of the variables, we constructed a predictive model of business academic research efficiency and tested the predictive accuracy of the model.

2 Business Academic Writing Assistant Model

2.1 Bert-based extractive summarization approach

In this paper, we propose a Bert-based extractive summarization method, which aims to achieve the generation of business academic resources in an automated way. This method mainly contains four layers, namely Bert vector representation layer, contextual feature extraction layer, contextual attention layer and key sentence summarization layer.

In the Bert vector representation layer, the feature vectors of business academic texts are extracted using the Bert model to solve the problem of multiple meanings of words and to obtain context vector representations that are more in line with business features. Using Bert model can obtain the deep semantic information in business academic and extract the key sentences more accurately. In addition, the input part and embedding layer are improved using the BertSum method, which makes the model adaptable to multi-sentence summarization tasks. In the contextual feature extraction layer, BiGRU model is used. By using the BiGRU model, the contextual information in business academic texts can be better extracted and the accuracy of recognizing key sentences is improved. The context-enhanced attention layer determines the importance of each input representation by calculating the attention weights. Applying the computed results of the attention mechanism to the input representations makes the important parts receive higher weights, causing the model to focus on the key information in the academic text and accurately extracting the important details of the academic text. In the key sentence abstraction layer, the abstract key sentence classification layer is utilized to judge the sentences in the business academic resource text, and the sentence containing more key information is selected as the abstract result of the article, and the specific model is shown in Figure 1.

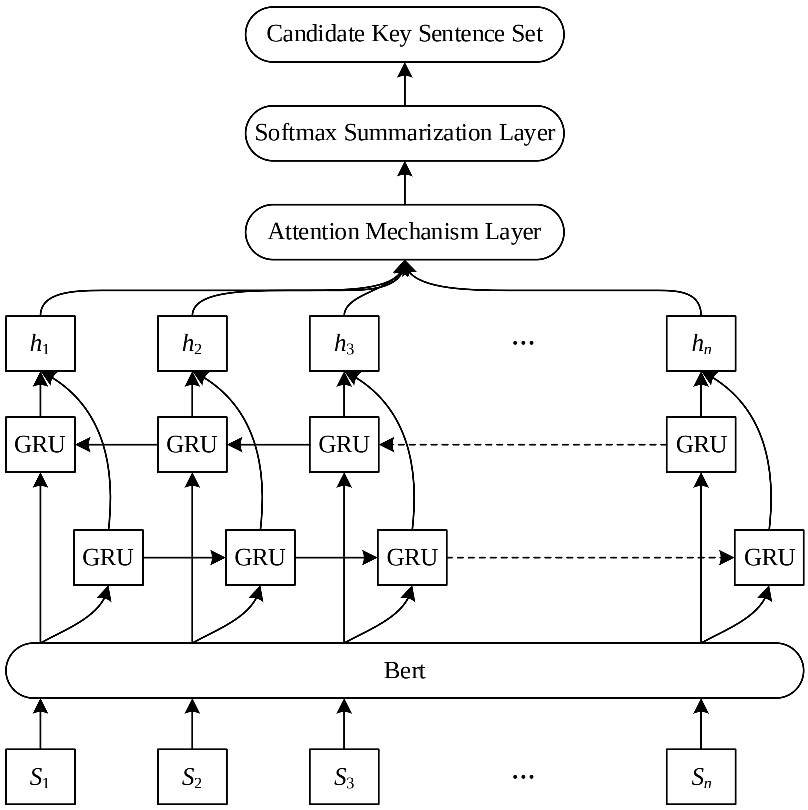


Figure 1: Extractive model

2.1.1 Bert-based vector representation layer

$[sent_1, sent_2, \ldots, sent_m]$ is used to denote a scholarly resource containing different paragraphs, where $sent_i$ is the i th sentence in the text of the scholarly resource, and extractive summarization can be defined as a way to indicate for each $sent_i$ is labeled 0/1, indicating whether the sentence should be included in the abstract or not. In this paper r_i is used to denote a reference tag.

The BertSum embedding layer is shown in Figure 2.Since Bert is based on word rather than sentence-level coding, and since Bert's segment embedding can only contain two sentence types and is not directly usable for multi-sentence summarization tasks at the time of input, the input portion of Bert and the word embedding were adapted to the summarization task.

A [CLS] marker was added to the front of each sentence in the academic resource and a [SEP] marker was added to the back to feed it into the Bert model. The position where each [CLS] marker is located corresponds to the sentence vector of each sentence. By using spacing symbols, it is possible to distinguish between multiple sentences in an academic paper. To distinguish the parity numbering of sentences, the segment embedding EA or EB is added to each sentence. e.g., for the sequence of sentences $\left[sent_1, sent_2, \ldots, sent_5\right]$, their segment embedding would be $\left[EA, EB, EA, EB, EA\right]$.

x_i is the representation of the sentence vector $sent_i$ for the position corresponding to the i th [CLS].

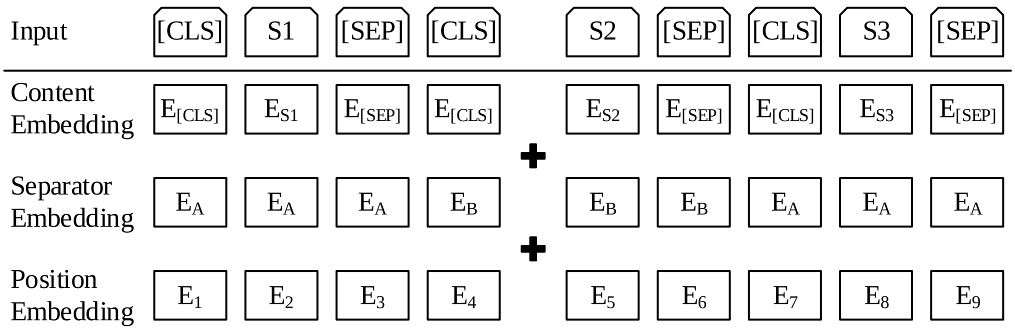


Figure 2: BertSum embedding layer

2.1.2 Contextual feature extraction layer

In order to better extract contextual information, this paper employs a bidirectional GRU model for sequence modeling of text to capture the dependencies of contextual words in long text sequences and to obtain a vector representation of the current moment. This computational process builds on the context vectors obtained from the context feature extraction layer. Specifically, in this paper, the two-way GRU model is used to model the text from both forward and backward directions to obtain more comprehensive contextual information. At each moment, the output vectors of the forward and backward GRUs are stitched together to form a comprehensive context vector representation. Eventually, a two-way GRU model modeling text sequences is obtained, which can capture the contextual information in long text sequences and provide richer semantic representations for subsequent tasks. The specific computational process is shown in Eqs. (1)-(3):

$$\overrightarrow{h_t} = GRU\left(h_{t-1}, x_t\right) \tag{1}$$

$$\overleftarrow{h_t} = GRU\left(h_{t+1}, x_t\right) \tag{2}$$

$$h_t = \left[\overrightarrow{h_t}, \overleftarrow{h_t}\right] \tag{3}$$

At moment t, the hidden state vector of the forward GRU is denoted as $\overrightarrow{h_t}$, and the hidden state vector of the reverse GRU is denoted as $\overleftarrow{h_t}$, which are obtained from the input vector x_t at the current moment and the hidden state vectors of the previous moment in the current direction h_{t-1} and h_{t+1}. In order to synthesize the information from both directions, in this paper, $\overrightarrow{h_t}$ and $\overleftarrow{h_t}$ are spliced together to obtain the hidden layer state vector h_t at the current moment. This vector contains the contextual information obtained from both directions and can provide a richer semantic representation for subsequent tasks.

2.1.3 Upper and Lower Enhanced Attention Layers

With the increase of model parameters, the expressive ability of neural networks increases, but it also leads to the problem of information overload. In order to solve this problem, the introduction of the attention mechanism can assign weight parameters so that the model focuses on the key information and reduces the attention to the low relevance information, which improves the efficiency of the algorithm.

The context-enhanced attention layer is an important component in the model, which calculates the attention distribution of the input text based on the contextual information. This mechanism simulates the process that humans will focus on key parts based on the current contextual information when reading and understanding text. By introducing the Attention mechanism, the model can extract more direct semantic dependencies by focusing on the key information in the data during the training process and reducing the attention to irrelevant or unimportant information. In this paper, the Attention mechanism is introduced on the basis of BiGRU network, which can encode text sentences by calculating the weights of different feature vectors.

Specifically, the Attention mechanism assigns weight parameters to each element according to the importance of the information, and these weights are called Attention values. The process of calculating the attention value includes the following steps: first, the attention distribution of the input information is obtained by calculating the attention score function; then, the attention score function is numerically transformed using the normalized exponential function in order to obtain the normalized weight coefficients; finally, the input information is weighted and summed according to these weight coefficients, so as to obtain the corresponding attention representation. The Attention layer is calculated as in Eqs. (4)-(6).

$$e_i = v_i \tanh\left(W_i h_i + b_i\right) \tag{4}$$

$$a_i = \frac{\exp\left(e_i\right)}{\sum_{j=1}^{n} e_j} \tag{5}$$

$$S = \sum_{i=1}^{n} a_i h_i \tag{6}$$

In the above equation, v_i represents the parameter vector, W_i represents the weight matrix, b_i represents the bias vector, h_i represents the hidden initial state of the input, e_i represents the attention score corresponding to h_i, and a_i represents the weight value of h_i, and the feature vector obtained after the calculation of the attention mechanism is denoted as S.

2.1.4 Key sentence summary layer

Abstract key sentence classification layer plays an important role in the model, and its main purpose is to classify and score the sentences in the text of academic resources in order to determine whether the current sentence has more key information and whether it is suitable as a candidate abstract sentence. By applying the $softmax$ function to the feature vector S, the probability distribution of the prediction result of the current sentence can be obtained, so as to classify and score it, as in Equation (7):

$$\hat{Y}_i = \sigma\left(W_o S + b_o\right) \tag{7}$$

In addition, to further improve the quality of the generated summaries and to reduce redundancy, the model employs Trigram Blocking. When given a selected summary S and a candidate sentence c, if there are three consecutive overlapping words between them, the processing of the candidate sentence c is skipped. This processing strategy helps to avoid repetitive information and ensures that the generated summaries are more concise and diverse.

2.2 Writing Generation Methods Based on Business Scholarship

2.2.1 Content selector

The main function of the content selector is to extract key content from the text of the scholarly resources in each section. This module is designed to achieve two important objectives: on the one hand, by extracting the key content, the length of the text entered into the text rewriter can be significantly reduced, thus reducing the model's burden of modeling long text; on the other hand, the information is filtered to enhance the model's ability to obtain key information.

In order to achieve this goal, two extraction methods are designed in this module. The first is a BertSum-based selector, BertSum is a pre-trained extractive model based on Transformer, which has a unique advantage in capturing key information in the input text. The second is a rule-based selector, where key information is selected from academic resource texts based on predefined rules. The above two approaches to content selection help to explore the impact of different selection methods on the three-stage model.

BertSum-based selector: for a given academic resource text, the input embedding for each token in each text record consists of a token embedding z^{token}, a fragment embedding z^{seg}, and a position embedding z^{pos} in the input sequence as in equation (8):

$$z_l = z_l^{token} + z_l^{seg} + z_l^{pos} \tag{8}$$

The input embedding of each token is then passed to the BERT model to obtain a sentence-level vector representation T_i. For each sentence $sent_i$, its vector representation T_i is input into a simple classifier that computes the final prediction score $\hat{Y}_i$ and ranks them according to the final scores, selecting the ones with the highest scores as the generated extracted summaries. This simple classifier adds a linear fully connected layer to the BERT output and uses a sigmoid function to obtain the predicted scores, where W_o, b_o are learnable parameters as in equation (9):

$$\hat{Y}_i = \sigma\left(W_o T_i + b_o\right) \tag{9}$$

The training of this model requires supervised data, which needs to be acquired by heuristic rules, and the greedy algorithm is used in this part to extract sentences from the articles. Firstly, the most frequent sentence in the text of the academic resource is selected to be added to the candidate set, then the selection from the input is continued to ensure that the ROUGE score of the selected target set increases until the condition cannot be met. The sentences corresponding to the obtained candidate set are set as 1-label and the rest as 0-label.

Assuming that Y_i represents the true label (0 or 1), the optimization objective of the module is to minimize the binary cross-entropy loss between $\hat{Y}_i$ and Y_i, i.e., as in Equation (10):

$$L_B = -\sum_{i=1}^{N}\left[Y_i * \log(\hat{Y}_i) + (1 - Y_i) * \log(1 - \hat{Y}_i)\right] \tag{10}$$

Rule-based selector: in order to investigate which rules are effective in selecting academic resource text records, this module tries to make ChatGPT play the role of a selector by setting appropriate hints to select key academic resource text records.

In this process, the fact that ChatGPT will start to generate errors when the number of output sentences exceeds 20 is found. Based on this, a rule-based selector (RS) is designed in this module.

2.2.2 Text rewriters

The main goal of the text rewriter is to transform the important arguments of the academic text extracted by the content selector $\tilde{C}_i\left(i = 1,2,3,4\right)$ into the corresponding complete academic text $\tilde{R}_j\left(j = 1,2,3,4\right)$. This task requires a strong learning and generative capability of the model. The pre-trained Transformer-based model has achieved significant results in various generative tasks. Increasing the number of layers in the Transformer stack improves performance, but also increases training time and slows down generation.

The CPT model is a variant of BART and consists of a deep shared encoder (S-Enc) and two shallow decoders (U-Dec, G-Dec). Compared to the BART model of the same size, the CPT model employs only the shallow decoders, and thus inference generation is faster. Since the length of the model input is up to 2048 tokens, which is far more than the 512 tokens that the existing training models can handle, it poses a challenge for both training speed and generation speed.

To improve efficiency, this study first extends the CPT-Large model by expanding the maximum position length, encoding layer, and decoding layer to 2048 tokens.Subsequently, the extended CPT-Large is fine-tuned using long input text (2048 tokens) and the fine-tuned model is used as a text rewriter. This refinement enables the processing of long text inputs while maintaining the model generation capability. The model structure of the text rewriter is shown in Figure 3.

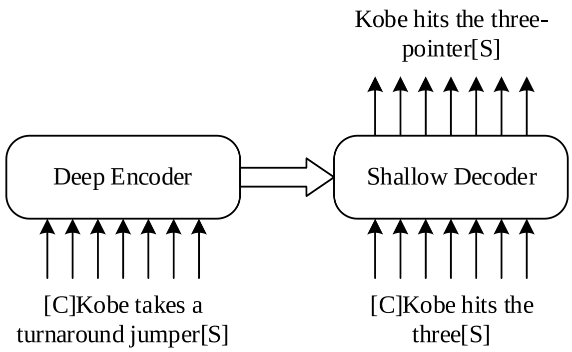


Figure 3: The model structure of the text rewriter

Specifically, the deep encoder consists of 20 layers of Transformer coding ends with fully connected self-attention mechanisms, while the decoder consists of 4 layers of Transformer decoding ends with masked self-attention mechanisms. The number of HEADs computed for each layer of multi-head attention is set to 16, and the dimension of the model's hidden state is 1024.

The encoding end of the Transformer is shown in Fig. 4 and consists of a self-attention layer and a fully connected layer. It is worth noting that there is more than one layer of this self-attention, and the model uses a multi-head attention computation, which stitches together the outputs of multiple self-attention and then undergoes a single linear transformation to obtain the final output.

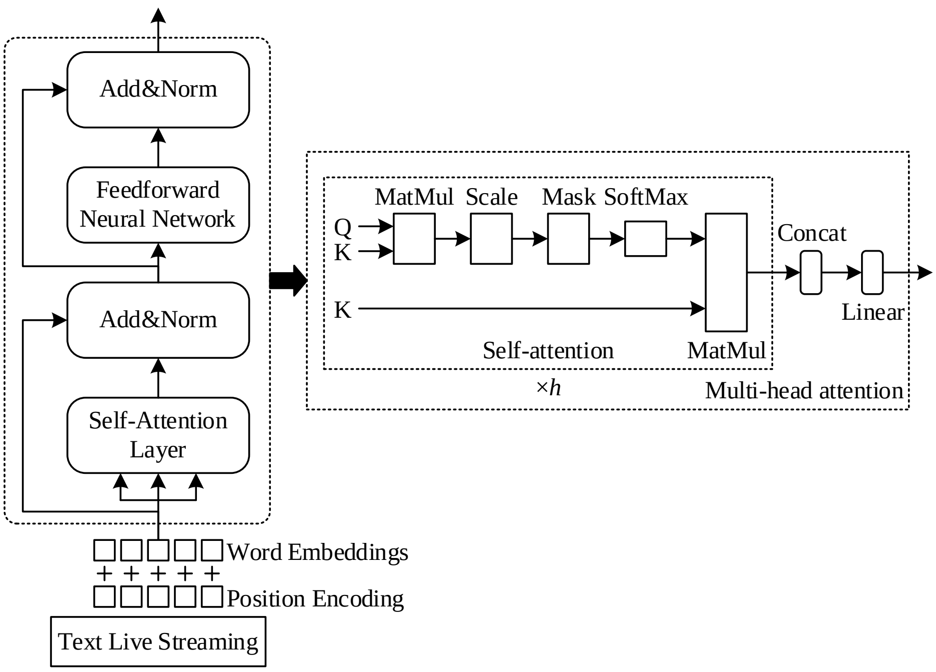


Figure 4: The encoding structure of the Transformer

For each text record, its embedded representation $X \in \mathbb{R}^{L \times d}$ (where L denotes the length of the text live record and d is the dimension of the model's hidden state) can be obtained, as well as the initial hidden state h_0, and the computation of a single self-attention is as in Eqs. (11)-(13):

$$Q = XW^{q} \in \mathbb{R}^{L\times d_k} \tag{11}$$

$$K = XW^{k} \in \mathbb{R}^{L\times d_k} \tag{12}$$

$$V = XW^{v} \in \mathbb{R}^{L\times d_v} \tag{13}$$

First, the input vector representation X is computed with the linear transformation matrices W^q, W^k, W^v (their dimensions are all $\mathbb{R}^{d\times d_h}$, where $d_h = d_k = d_v = d / h$) to obtain Q, K, V (denoting query vectors, key vectors and value vectors, respectively), with Eq. (14):

$$Attention(Q, K, V) = soft\max\left(\frac{QK^T}{\sqrt{d_k}}\right)V \tag{14}$$

Next, the computation of attention scores is carried out to obtain the correlation scores of each query vector with all key vectors using the dot product operation of Q and K. The result of the dot product is scaled (divided by the square root of the feature dimension) to ensure that the gradient is more stable during the training process.Mask is used to control the attentional correlation relationship between words. The attention scores are then normalized by a softmax function to obtain the attention weights. These weights indicate how much attention each query vector pays to all key vectors, i.e., the importance with each position. Finally, the attention weights are multiplied with the value vectors and the result is weighted and summed to obtain the output representation of the self-attention mechanism. For each self-attention, the above process is followed, and the computation of the lth layer coding part of the text rewriter encoder is as in Eqs. (15)-(18):

$$H_i = Attention\left(QW_i^Q, KW_i^K, VW_i^V\right) \tag{15}$$

$$MHA = Concat\left(H_1, H_2, \ldots, H_h\right)W^h \tag{16}$$

$$h_l^M = LayerNorm\left(h_{l-1} + MHA\left(h_{l-1}\right)\right) \tag{17}$$

$$h_l^E = LayerNorm(\left(h_l^M + FFN\left(h_l^M\right)\right) \tag{18}$$

where $W_i^Q, W_i^K, W_i^V \in \mathbb{R}^{d\times d_h}$ are learnable parameters, $W^h \in \mathbb{R}^{d\times d}$, MHA denotes the MultiHeaded Self-Attention Layer, and FNN denotes the Forward Feedback Network Layer (a two-layered fully-connected layer, with an activation function for the first layer as ReLU, the second layer does not use an activation function). The output of the coding side of the text rewriter $E \in \mathbb{R}^{L\times d}$ can be obtained after the same computation in 20 layers.

Compared to the coding side, the decoding side of the Transformer has an additional layer of cross-attention that interacts with the output of the coding side, and here the self-attention layer employs a masking operation. The computation of the decoding part of the lth layer of the decoder is shown in Eqs. (19)-(21):

$$h_l^A = LayerNorm\left(h_{l-1} + MHA\left(h_{l-1}\right)\right) \tag{19}$$

$$h_l^C = LayerNorm\left(h_l^A + Cross\text{-}Attention\left(h_l^A, E\right)\right) \tag{20}$$

$$h_l^D = LayerNorm\left(h_l^C + FFN\left(h_l^C\right)\right) \tag{21}$$

Assuming that the predicted probability of the text rewriter ending up on the word list is $P(\hat{y})$, and the target text is represented as $G=\left(y_0, y_1, \ldots, y_n\right)$, the objective optimization function of the model fine-tuning is shown in equation (22):

$$L_r = -\sum_{i=1}^{n} \log P_i\left(\hat{y}_i = y_i \mid x_0, \ldots, x_m; y_0, \ldots, y_{i-1}\right) \tag{22}$$

3 Performance Validation of the Business Academic Writing Assistant Model

3.1 Effects of language use

In this section, the method of comparing the differences of word chunks in the Business Academic Writing Assistant model and the expert scholars' business journal papers is used to assess the effectiveness of the language use of the Business Academic Writing Assistant model. For the convenience of the study, Corpus B was formed based on the business journal papers of expert scholars, and Corpus C was formed based on the business academic studies generated by the Business Academic Writing Assistant model.

The business academic resources in Corpus B and Corpus C were searched, and combing through the search results revealed that there were 10 common word blocks between the method and the corpus of business academic specialists. The results of the significance analysis of the 10 shared word blocks using the log-likelihood ratio are shown in Table 1.The 10 shared word blocks accounted for a total of 7.36% of the total number of expert scholars in Corpus B, and 9.78% of the total number of business academic writing assistants' models in Corpus C, which suggests that there is a potential consistency between the two in the selection and use of the types of professional nouns.

Table 1: The usage frequency of common word blocks in corpora B and C

Serial number	Common word block	Frequency		LL	*p*
		B	C		
1	an emerging class of	6	5	-0.576	0.358
2	for the development of	8	9	-0.576	0.358
3	here we report a	3	10	-7.325	0.007**
4	on the surface of	7	10	-1.947	0.243
5	a wide range of	4	4	-0.114	0.802
6	in the presence of	4	4	-0.114	0.802
7	for the first time	5	8	-1.947	0.243
8	an order of magnitude	6	4	0.045	0.914
9	for the synthesis of	5	5	-0.114	0.802
10	a crucial role in	7	5	-0.576	0.914
Proportion of the total(%)		7.36	9.78	-	-

Note:*p<0.05,**p<0.01,***p<0.001,the same below

Further, the top 10 high-frequency word chunks of Corpus B and Corpus C are shown in Table 2, which shows that 2 of the top 10 high-frequency word chunks of Corpus B contain of-phrase structures, accounting for 20.00% of the total number of chunks. In Corpus C, there are 5 high-frequency word blocks in the first 10 high-frequency word blocks containing of-phrase structure, accounting for 50.00%. In addition comparing Table 1 with Table 2, the Business Academic Writing Assistant model was able to generate word chunks that did not appear in the expert scholars to introduce the research, such as “thisworkrepresentsa/an” and "theresearchersdevelopeda/an". Overall, although the business academic research written by the expert scholars is more in line with the English academic writing standard, the Business Academic Writing Assistant model has been equipped with strong linguistic comprehension and generative abilities to skillfully handle natural language in the business academic context.

Table 2: High-frequency word blocks from Corpus B and Corpus C

Rank	B	Frequency	C	Frequency
1	represents a significant advancement	49	here we report a	50
2	the researchers developed a/an	47	the presence of a	46
3	this study introduces a/an	45	of the two components	43
4	this work represents a/an	44	for the development of	41
5	a promising approach to	39	we are reporting a	40
6	opens new avenues for	37	here we report the	35
7	demonstrates the potential of	29	for the synthesis of	33
8	with potential applications in	27	a crucial role in	21
9	the critical role of	24	a wide range of	19
10	an innovative approach to	16	here we show that	15

The frequency of the four main academic language structures (noun chunks, prepositional chunks, verb chunks, and subordinate clause chunks) in the statistical corpora B and C, and the results of their log-likelihood ratios and significance are shown in Table 3. Overall the distribution of the Business Academic Writing Assistant Model Corpus C in the use of the four main academic language structures is more even, accounting for about 25.00%, and is more consistent with the use of Expert Scholars' Corpus B There is no significant difference ($p>0.1$), i.e., the Business Academic Writing Assistant Model's use of linguistic terms and structures has largely reached the standard of academic research in business specialties.

Table 3: The distribution of word block structures in Corpus B and Corpus C

Chunks	Frequency and proportion		LL	*p*
	B	C		
Noun	304(25.33%)	319(26.58%)	-0.607	0.557
Prepositional	291(24.25%)	305(25.42%)	-0.491	0.667
Verb	317(26.42%)	304(25.33%)	-0.235	0.697
Clause	288(24.00%)	272(22.67%)	-0.535	0.908
Total	1200(100%)	1200(100%)	-0.341	0.763

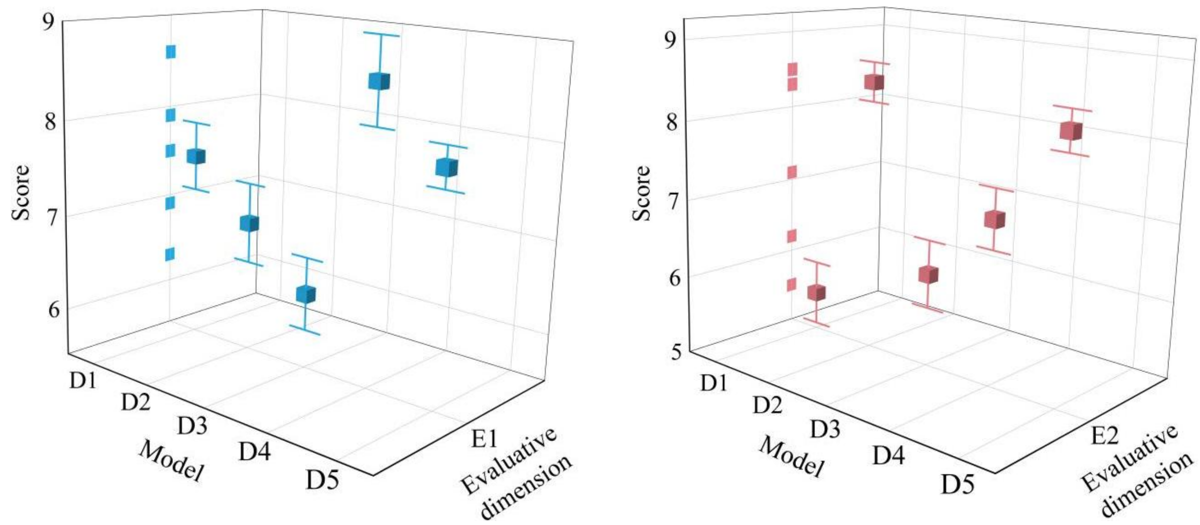
3.2 Text generation effect

Four current commonly used text generation models: (D1) RNNPG, (D2) PPG, (D3) CVAE, and (D4) MixPoet are selected as comparison models to manually evaluate the (E1) fluency, (E2) thematic consistency, (E3) rhythm, and (E4) aesthetics of the generated text.The results of the manual evaluation of the four comparison models and (D5) the model of this paper are shown in Table 4 , where the full score of all four evaluation dimensions is 10 points. From the perspective of a single evaluation dimension, all four comparison models have their own focus. (D1) The RNNPG model generates textual content with outstanding (E3) rhyme performance (8.6), but is extremely poor at maintaining (E2) thematic consistency (5.8). The (D2)PPG model, on the other hand, excels at (E2)thematic coherence (8.2), and the remaining three performances are more consistent (6,7) but all are weaker. (D3)The CVAE model generates text with more excellent (E4)aesthetics (8.3), while the remaining three performances have a passing level. The (D4) MixPoet model not only excels in generating text with (E1) fluency, but also the remaining three items with levels between (6.9,7.1). In contrast, although (D5) the model in this paper does not have particularly outstanding dimensional performance, it is able to deal with (E1) fluency, (E2) thematic coherence, (E3) rhythm, and (E4) aesthetics of the generated text in all aspects, focusing on the range of (7.8,8.0), and the average score of manual evaluation (7.85) is the highest among the five models.

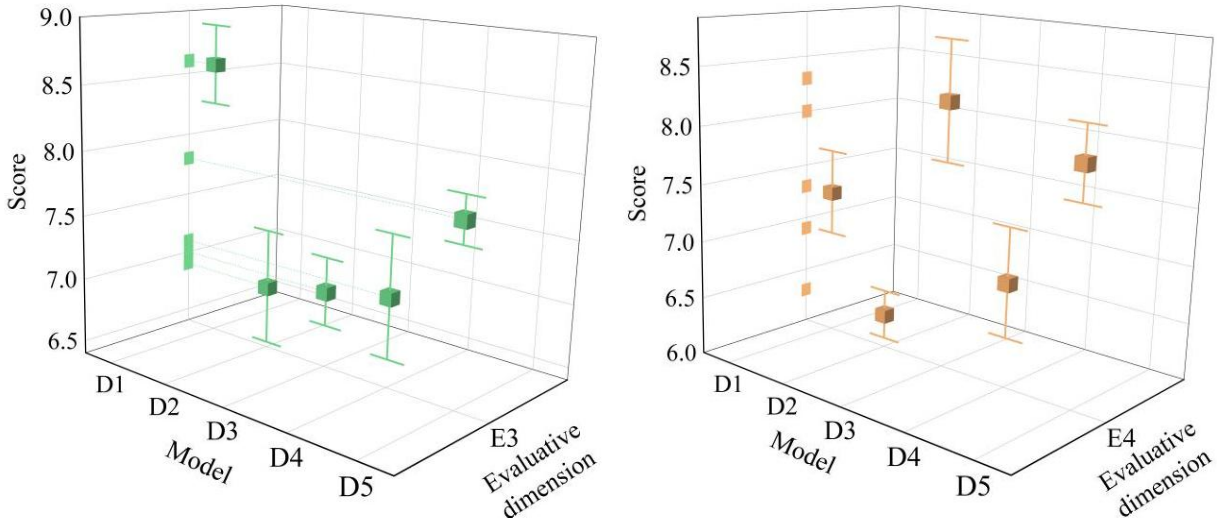
Table 4: Manual evaluation results

Model	E1	E2	E3	E4	Average
D1	7.2	5.8	8.6	7.3	7.23
D2	6.7	8.2	6.9	6.3	7.03
D3	6.5	6.4	7.0	8.3	7.05
D4	8.2	7.0	7.1	6.9	7.25
D5	7.9	8.0	7.8	8.0	7.85

Using the ChatGPT model also from four dimensions to evaluate the effect of five models to generate text is shown in Figure 5(a)-(d), the overall ChatGPT model for the five models to generate text effect evaluation and manual evaluation is more consistent with no significant gap, and from this, we can see that (D5) this paper's model is not only more comprehensive, and its variance (<0.50) is lower, relatively stable.



(a) E1 (b) E2



(c) E3 (d) E4

Figure 5: The evaluation results of ChatGPT

4 An Empirical Study of Academic Efficiency Improvement

In this paper, Logistic regression model is selected as a research and analysis tool, research samples are selected and data are counted and screened, research variables are set and research preparation is completed. On this basis, the role and effect analysis of the influence of business academic writing assistant on the efficiency of business academic research are developed in detail.

4.1 Logistic regression model

Logistic regression model is a commonly used statistical analysis model for dealing with binary classification problems. It maps a linear combination of independent variables into the $[0,1]$ interval through a logistic function (Logistic function), which represents the probability of occurrence of an event.

(1) Model form

Suppose there is a binary classification problem with input features $X=(X_1,X_2,\ldots,X_p)$, and the output is a binary variable Y, and the Logistic regression model takes the form of equation (23):

$$P(Y=1|X)=\frac{1}{1+\exp\left[-\left(\beta_0+\beta_1X_1+\beta_2X_2+\ldots+\beta_pX_p\right)\right]} \\ P(Y=0|X)=1-P(Y=1|X) \tag{23}$$

where $P(Y=1|X)$ denotes the probability that the output is 1 given the input X, and $P(Y=0|X)$ denotes the probability that the output is 0. The $\beta_0,\beta_1,\ldots,\beta_p$ are the parameters of the model, which denote the effect of the feature X on the binary variable Y.

(2) Logistic function (sigmoid function)

The logistic function, also known as the sigmoid function, in a logistic regression model converts the results of a linear combination into probability values between $[0,1]$ in the mathematical form of equation (24):

$$g(z) = \frac{1}{1+\exp(-z)} \tag{24}$$

where $z = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \ldots + \beta_p X_p$ is the result of a linear combination.

(3) Parameter estimation

Maximum likelihood estimation (MLE) is commonly used to estimate the parameters of a logistic regression model. The goal of maximum likelihood estimation is to find a set of parameters that maximize the probability of occurrence of the observed data.

(4) Model Evaluation

The performance of a Logistic regression model can be evaluated by a series of metrics including accuracy, recall, precision, etc.

4.2 Study design

A total of 236 master's and doctoral students (including postdoctoral students) enrolled in business majors of three universities in Region F were selected as the experimental subjects, and the academic research of the experimental subjects was supplemented with business academic writing assistants for a period of six months, and the research was carried out by means of offline interviews and questionnaires.

A total of 15 multiple-choice questions were designed in the questionnaire, which mainly examined the role and effect of the business academic writing assistant in improving the efficiency of their academic research from the levels of personal situation, personal utility, and overall effect and efficiency. The analysis was carried out according to the procedure of "Interview - Questionnaire Completion - Data Entry - Empirical Analysis - Response".

After interviewing 236 students to obtain their overall academic research situation, the questionnaires were distributed to the students for completion. Three invalid questionnaires were excluded, and 233 valid questionnaires were obtained, with a validity rate of 98.73%. The data from 233 valid questionnaires were entered into the system to obtain the sample data set for the study.

4.3 Variable Description and Statistics

The efficiency of academic research in business was set as the dependent variable, and seven research variables (H1-H7) as the independent variables.The basic content and coding of the seven research variables are as follows:

(1) (H1) Gender: 0 means female and 1 means male.

(2) (H2) Academic experience: 0 indicates that both of the master's degree are in the same major, 1 indicates that two of the master's degree are in the same major, and 2 indicates that both of the master's degree are in different majors.

(3) (H3) Current academic progress: 0 indicates the preparation and design stage, 1 indicates the experiment/research and data collection and analysis stage, 2 indicates the finishing and writing stage, and 3 indicates the revision and review stage.

(4) (H4) Own academic output: 0 indicates yes and more, 1 indicates yes but less, 2 indicates no.

(5) (H5) Proficiency with generative AI academic writing assistants: 0 indicates very familiar, 1 indicates average, and 2 indicates not used.

(6) (H6) Proficiency in applying the generative AI academic writing assistant to business

academic research: 0 indicates proficiency in applying it to all aspects of academic research, 1 indicates that it will be used in specific aspects/stages of research, and 2 indicates that it will be used less/not at all.

(7) (H7) Usefulness of generative AI academic writing assistants in business academic research: 0 indicates resource searching, 1 indicates asking questions and inspiring thinking, 2 indicates data integration and analysis/knowledge point framework generation, and 3 indicates assisting with writing (including improving, generating, translating, etc.).

The variables of the analyzed research sample are shown in Table 5, where the mean value of the variable (H1) gender is 0.553, and the overall gender distribution is more balanced. The mean value of (H2) academic experience is 1.075, and two of the sample subjects have the same specialty in their bachelor's and master's degrees in the majority of cases.

Table 5: Statistics of variables

Variables	Mean	Standard deviation
H1	0.553	0.128
H2	1.075	1.758
H3	1.984	1.636
H4	0.939	0.578
H5	0.495	0.416
H6	1.185	0.771
H7	1.451	0.639

In addition, the constant term was set to be the students' academic research efficiency after the Business Academic Writing Assistant model assisted academic research with the content number H. The content is: 0 means some degree of improvement, 1 means some improvement, and 2 means no significant improvement.

4.4 Predictive modeling and testing

Combining the content of the interview and the questionnaire can determine the academic research efficiency situation of the research sample, using Logistic regression model to regression analysis of the sample constant term and the seven independent variables, the parameter estimation results are shown in Table 6, according to which to construct the predictive model of the effect of generative AI academic writing assistant on the efficiency of academic research in business.

Table 6: Parameter estimation result

Factor		Parameter		Standard error	Wald value	*df*	*p*	95% confidence interval	
		Serial number	Value					Lower limit	Upper limit
Constant	0	α_0	-7.955	5.855	5.943	1	0.036	-9.045	2.933
	1	α_1	-4.313	5.945	0.881	1	0.018	-1.425	14.653
	2	α_2	-5.277	5.535	1.437	1	0.195	-13.623	2.178
H1		β_1	-4.321	3.071	0.683	1	0.311	-10.438	-0.12
H2		β_2	0.255	0.876	0.241	1	0.024	-6.557	8.598
H3		β_3	-0.82	0.391	0.255	1	0.522	-3.163	14.886
H4		β_4	-2.682	3.645	0.213	1	0.019	-0.384	10.384
H5		β_5	-3.512	0.336	1.873	1	0.042	-0.013	13.763
H6		β_6	-8.065	0.481	1.077	1	0.024	-13.292	1.859
H7		β_7	0.182	0.742	1.862	1	0.013	-7.495	9.805

Using the constructed prediction model to predict the academic research efficiency of the 236 research samples after using this paper's business academic writing assistant, the prediction results overlap with the actual data as shown in Table 7.The accuracy of the model's prediction for the situation of actually being in the 0: somewhat improved situation is 93.75%, the accuracy of the prediction for the situation of actually being in the 1: somewhat improved situation is 82.11%, and the accuracy of the prediction for the situation of actually being in the 2: not significantly improved situation is 81.63%. The prediction accuracy for the case of actual at 2: no significant improvement is 81.63%. Overall, the model's prediction accuracy (>80.00%) meets the practical needs and is better at predicting situations where the efficiency of academic research has improved.

Table 7: Model prediction accuracy test

Predicted value			0	1	2
Actual value	0	Number	60	4	0
		Proportion(%)	93.75	6.25	0.00
	1	Number	15	101	7
		Proportion(%)	12.20	82.11	5.69
	2	Number	6	3	40
		Proportion(%)	12.24	6.12	81.63
Accuracy rate(%)			93.75	82.11	81.63

5 Conclusion

In this paper, we have designed a model of business academic writing assistant containing basic Bert's extractive summarization method and business academic based writing generation method. The filtering and use of business academic word chunks in the model-generated text has some similarity with that of professional experts and scholars, and it is able to generate the content of word chunks that professional experts and scholars have less/never employed. The distribution of the use of the four main academic language structures is not only more uniform (25.00%) but also not significantly different from that of professional experts and scholars ($p>0.1$). The content of the generated text was evaluated by the manual evaluation and ChatGPT model in the four dimensions of fluency, thematic consistency, rhythm and aesthetics, and was in the higher range of (7.8,8.0) with a variance of <0.50, which is both linguistic effectiveness and stability, and is able to satisfy the current needs of academic research in the business discipline.

Taking the business academic research efficiency as the dependent variable, the business academic research efficiency prediction model was constructed based on the results of the regression analysis of the data of the seven independent variables of the research samples, and the overall accuracy of the model in predicting the academic research efficiency of the samples was 80.00% and above.

The Business Academic Writing Assistant model relies on its powerful functions of language optimization and content generation, which can shorten unnecessary time expenses for business academic research. At the same time, the combination of the prediction model effectively monitors the effectiveness of the Business Academic Writing Assistant model in assisting business academic research, which facilitates the adjustment and planning of academic research and opens a new chapter of business academic research in the era of AI.

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