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Research on the Application of Innovative Thinking in Secretarial Writing Practice

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Abstract When doing secretarial writing, innovative thinking is even more crucial to write articles that can communicate with supervisors and subordinates and have excellent communication effects. In this paper, we first design the pre-trained word vector algorithm to project all the word vectors into the same semantic space, so that there is a distance relationship metric between words. Then a long and short-term memory network is introduced for processing the text, and a bi-directional LSTM network structure is used to do the segmentation of the secretary writing text, realizing the construction of the innovative thinking scoring model of secretary writing based on machine learning. Then the model is used to analyze the innovativeness of secretarial writing of two types of volunteers: public office affairs secretaries and business affairs secretaries, and finally a controlled test of innovative thinking to improve secretarial writing is conducted. It was found that the three groups of public office type affairs secretaries were 2.21%, 3.89%, 17.65% and 7.98%, 10.19%, 16.46% in the percentage of grammatical rhetoric and expressive skill innovations, respectively, and the high level group had more innovative content in grammatical rhetoric and expressive skill than the remaining two groups. The degree of innovativeness in writing theme intention of business secretaries is 9.32%, 16.29% and 29.75%, and business secretaries can be more flexible and free to use innovative thinking in the selection of writing themes. They have more innovative thinking in the selection of writing topics than the public service business secretaries. This study provides a new method to improve innovative thinking in secretarial writing, and to improve the efficiency and writing quality of secretarial writing.

Index Terms rnn, transfer learning, text segmentation, secretarial writing

1. Introduction

Secretarial staff to serve the leadership, play the role of staff and assistant, is to grasp the content of the writing of this fundamental, this key [1]. Content contains ideas, information, values and other human thinking and emotional activities can be expressed in a variety of styles, but ideas, information, values and these core elements are the audience to accept the content of the product of the fundamental reasons [2]. Therefore, continuous innovation in content, grasp the leadership intentions, to meet the needs of the masses, to build a bridge between the leadership and the masses, has become the soul of secretarial writing. A good research report can give birth to a scientific decision-making, an excellent summary of experience can create a huge productivity, fundamentally, it is the research report, summary of experience these secretarial writing content in play [3-4].

With the deepening and development of reform and opening up, the social life is more and more rich, the secretarial writing content involves a wider and wider range, from the decision-making program, rules and regulations, research reports to the summary of experience, feedback, and promotion of the results of the whole management activities must be used in conjunction with the secretarial writing [5-6]. Such as

modern management of innovative management methods, add management links, etc., the content of the secretarial writing involved must be adjusted to adapt to the systematic, scientific management needs [7]. Even in daily life, secretarial writing with the diversity of life and the formation of increasingly rich content. This synchronization with the development of the times, synchronization with the work of the leadership, fully implement the intentions of the leadership, fully reflect the wishes of the masses of the requirements, but also precisely the content of the secretarial writing of the innovation of the outstanding performance and the essence of the requirements [8].

Innovation, is the knowledge economy era on the special requirements of the quality of the secretary. An excellent secretary is an excellent staff, and the core of the staff is innovation. Secretary writing innovation ability of high and low, decide the size of the role of the secretary staff. No new ideas, new approaches, it is impossible to assist in the decision-making process to send a bright spark. Secretarial writers to play a greater role in the leadership decision-making process, it is necessary to adhere to innovation [9]. In order to meet the challenge of rapid progress in science and technology and the rapid emergence of knowledge-based economy, secretarial

writers should adhere to the actual starting point, dare to break through the stereotypes, to do a good job of secretarial work in the spirit of innovation, to be pioneering and progressive rather than stick to the old ways, to strive to be the first and not be willing to live in the back of the people, a bold breakthrough rather than adhere to the stereotypes, and rise to the challenge rather than shrinking back from it [10].

Only by synchronizing with economic development and social life can secretarial writing serve the leaders and their decision-making, and ultimately achieve the purpose of serving the people, thus reflecting its value of service and innovative requirements. As long as secretaries keep up with the new trend of the times, reflect the voices of the masses, and focus on solving the real problems, they can make secretarial writing always write and keep pace with the times. Wahyuni, S proposed a blended learning model to help improve students' writing skills and validated it by using a controlled experimental method, which confirms that the proposed blended teaching model significantly contributes to the improvement of the students' writing skills [11]. Alpern, S et al. analyzed and discussed the issue of secretarial hiring and concluded that the more expertise and ideas a secretarial candidate has in the field of leadership work and areas of interest, the more competitive he or she is [12]. Granado-Peinado, M et al. optimized and innovated the methodology of teaching writing in Spanish colleges and universities, with the optimization oriented towards transferring the focus of the teaching to the students in order to improve their critical thinking and argumentative writing skills [13]. Barczak, G summarized the different types and styles of papers in journals and explained three types of reviews, including narrative reviews that explain the subject knowledge of a paper, systematic reviews that comprehensively locate and examine a specific issue, and meta-analytic reviews that describe statistical methods for quantitative results [14]. Limpo, T. et al. empirically explored how scribing skills in the writing process affect writing fluency and text quality, based on an instructional experiment stating that more skillful transcription skills support students to write more text and words fluently during the writing process [15]. Ober, T. M. describes ManuscriptBuilder, an online digital tool for assisting in the writing of student research reports, with the support of which students are more able to write high-quality text reports [16]. Matsumoto, Y. An in-depth excavation and examination of material content and material application on multilingual writing classroom instruction pointed out that there are communication barriers and comprehension bias problems between students and instructors in terms of material use, and these findings can help to understand teacher-student interactions about materials in the writing classroom [17]. Goode, et al. conducted a pedagogical experiment to investigate the differences between blended learning (BL) and face-to-face teaching (FTF) in teaching effectiveness in writing and critical thinking in writing classrooms, and based on the results of the experiment, it was found that there was no significant difference in instructional modes, but there was a significant gap in teacher level indicators [18].

In this paper, we first construct a scoring model for creative thinking in secretarial writing based on machine learning. A pre-trained word vector algorithm is designed to encode syntactic and semantic information into dense vectors to solve the dimensional catastrophe and semantic divide problems caused by solo thermal encoding and to save the memory overhead of encoding computation. Then recurrent neural networks are introduced for text segmentation, followed by transfer learning, which is trained using a source-domain combination method to apply knowledge from the source domain to the target domain. After the model construction is completed, 37 volunteers working as secretaries are invited to participate in the study, and the model is used to analyze the volunteers' secretarial writing works and verify the model validity. Finally, a controlled test is conducted to see whether the use of innovative thinking in writing can improve secretarial writing.

II. A Machine Learning-Based Model for Scoring Creative Thinking in Secretarial Writing

A. Creative thinking in secretarial writing

Regardless of the government administrative affairs secretary and enterprise business affairs secretary, innovative thinking ability is the core requirement ability to improve the level of work, work efficiency. In secretarial writing, innovative thinking is the key to writing articles that can communicate with supervisors and subordinates and disseminate excellent results. Can be from the following angles to enhance the application of secretarial innovative thinking in writing.

1) Enhance the secretary's ability to think differently

Divergent thinking is an important part of innovative thinking, the secretary must pay attention to the exercise of divergent thinking ability, so that the secretary in thinking and writing to get rid of the limitations of conventional thinking, breakthrough thinking stereotypes, looking for innovative writing direction. To attach great importance to the Secretary of the training of divergent thinking skills, so that the Secretary from a small perspective, see the unseen, from a small perspective to reflect the big issues, so that the intention of novelty. This can achieve the training effect of innovative thinking, the secretary's writing ability and innovative thinking ability will be improved accordingly, and help to improve the overall quality of secretarial writing.

2) Cultivate the reverse thinking ability of the secretary

Reverse thinking ability is an important method and means to optimize the innovative thinking ability of the secretary, in the writing work should pay attention to the secretary's reverse thinking ability training, thinking along the opposite direction, from the opposite side of the standpoint, personalized viewpoints for the content of the work, for the ready-made theory of the question, so as to make the secretary writing more innovative and thinking, and effectively improve the overall quality of writing. You can choose some of the more common

or long established training projects, the organization of the secretary from the perspective of reverse thinking training.

3) Cultivate the secretary's multi-directional thinking ability

The secretary's working thinking has potential, and scientific training and guidance for the secretary can mobilize the flexibility of the secretary's thinking, but also can make the secretary's innovative thinking ability to be significantly improved. Therefore, conscious attention can be paid to the cultivation and training of the secretary's multi-directional thinking ability, so that the secretary from different perspectives to examine the writing work, analyze the content of the work requirements, to find the appropriate writing ideas, and improve the effectiveness of writing.

In this paper, the evaluation of innovative thinking in secretarial writing practice is divided into five dimensions, which are: vocabulary innovation percentage, grammar and rhetoric innovation percentage, article structure innovation percentage, expression skills innovation percentage, and main idea intention innovation percentage.

Among them, vocabulary innovation refers to the use of non-customary vocabulary that is relevant to the development of the times and represents emerging technologies and concepts in secretarial writing. Grammatical and rhetorical innovation refers to the use of refreshing references and rhetorical devices, such as metaphors and prose, in secretarial writing. Innovative article structure refers to the use of new layout and structure in the design of article framework. Innovative expression technique refers to the use of diagrams, animation, two-way interaction, etc. in secretarial writing. Creativity of main idea refers to some free play and innovation of the main idea of writing under the premise of centering on the content of work.

B. Pre-trained word vectors and recurrent neural networks

1) Pre-training word vector algorithm design

Suppose there exists corpus $C = \{s_1, s_2, \dots, s_n\}$ containing n sentences, for the i rd sentence in the corpus, containing m words. The vocabulary list in the corpus is $W = \{w_1, w_2, \dots, w_u\}$, where u is the number of words contained in the vocabulary list, i.e., there are u words in the corpus that are not repeated. The traditional approach would represent the words in a solo thermal representation, where the dimension of each word vector is the same as the size u of the vocabulary list, and w_5^j would be represented as $v_5^j = [0, 0, 0, 0, 1, \dots, 0, \dots, 0]_{1 \times u}$, with only the 5th dimension informative and the rest of the dimensions uninformative, and the representation of the word vectors would become larger as the vocabulary list of the corpus u becomes larger. Obviously, using the uniquely hot coded representations will consume a lot of computational resources and the inter-relationships between words cannot be measured.

There are three representative word vector construction methods, namely, Word2vec, a context-based pretraining word vector construction method, Glove, a global corpus-based

pretraining word vector construction method, and BERT, a transformer-based pretraining model. Word2Vec is a model that uses a fixed-size sliding window to slide from the beginning to the end of the textual data, and in turn The context of the sliding $s_i = \{w_1^i, w_2^i, \dots, w_m^i\}$ window is extracted to predict the words to be predicted in the window, and the model of word vectors is trained by back-propagation. Glove is based on LSA and Word2Vec, and the model is trained using the co-occurrence matrix and the ratio property. The transformer-based pre-training model BERT is not essentially a model trained to train word vectors, but BERT has a well-coded representation of each word due to the transformer processing mechanism and sufficient corpus, and the word vectors have different representations with different contextual changes.

- a) Word2Vec: There are two training methods for Word2vec models, the Continuous Bag of Words (CBOW) model that predicts the middle word with known words on both sides within a sliding window, and the Skip-Gram model that predicts both sides with known middle words within a sliding window. The CBOW model consists of an input layer, a projection layer and an output layer, assuming that the current window contains word $[w_{t-2}, w_{t-1}, w_t, w_{t+1}, w_{t+2}]$, CBOW firstly uniquely hot encodes the window word as an input layer, the encoding dimension is the set of non-repeated word lists of the current corpus, and then accumulates and sums up the uniquely hot encoding of $[w_{t-2}, w_{t-1}, w_{t+1}, w_{t+2}]$ in the projection layer, and after that uses the summed up encoding as an input layer, and then goes to classify the predicted word for prediction by using the SoftMax function. The idea of Skip-Gram to train word vectors is opposite to that of CBOW, which uses the target word within the window to predict the words on both sides of the window, so the input of Skip-Gram is the uniquely hot encoding of the target word, and the output of Skip-Gram is the words on both sides of the window.
- b) Glove: Glove distinguishes itself from the problem of high computational complexity caused by the use of singular value decomposition in the latent semantic analysis method LSA. It relates word vectors and ratio properties through the ratio properties, establishes a loss function, and optimizes the least square loss using the Adagrad method. Distinguished from Word2Vec which trains word vectors based on local context, Glove uses a sliding window to count the frequency of word co-occurrences within a fixed window in the global corpus to construct the co-occurrence matrix. The co-occurrence matrix construction process is as follows, assuming that the co-occurrence matrix is X and its element is $X_{i,j}, X_{i,j}$ denoting the number of times words i and j appear together in a window. With a corpus $C = \{Tom, I, love, you, but, you, love, him\}$ and a glossary size $N = 6$, a window content is generated after one slide, assuming that the current sliding

window width is 5. Instead of using a neural network model, Glove constructs word vectors based on the ratio property, as shown in equations (1), (2), and (3):

$$\text{ratio}_{i,j,k} = \frac{P_{i,k}}{P_{j,k}} = \frac{\exp(v_i^T v_k)}{\exp(v_j^T v_k)}. \quad (1)$$

$$P_{i,k} = \frac{X_{i,k}}{X_i}. \quad (2)$$

$$X_i = \sum_{j=1}^N X_{i,j}. \quad (3)$$

$P_{i,k}$ denotes the probability that word k occurs in word i context, v_i, v_j, v_k denotes the vector representation of the current word i, j, k , X_i denotes the number of times word i occurs, and $X_{i,k}$ denotes the number of times word k occurs in i context.

- c) BERT: BERT as a pre-training model makes the word vectors generated by BERT more versatile due to its dynamic generation of BERT vectors, the advantages of the transformer structure, BERT bi-directional encoding and training based on large corpus data. The transformer encoder unit consists of two parts: a multi-head self-attention mechanism and a fully connected forward propagation network, both of which introduce residual connectivity and normalization ideas. The self-attention mechanism assigns weights to the input codes, and the codes after each self-attention mechanism are accumulated and passed into the forward network. The forward network normalizes the encoding and adds it to the incoming encoding, and then outputs it to the next transformer encoder unit. BERT is based on the processing of the transformer encoder to train the model, which is different from the GPT pre-training model, BERT is based on the MLM pre-training task to encode the bi-directional contextual information for the training, so the vectors of the BERT model are more generalized. model's vectors are more generalized.

2) Recurrent neural networks

Recurrent Neural Network (RNN) is a neural network structure created to process text or speech signals that have sequential relationships like sequence information. Recurrent neural network solves the problems of feed-forward neural network (FNN) which has no sequential information in its input, convolutional neural network which cannot extract global semantics, and traditional language model which occupies a large amount of storage resources, and it has a wide range of applications in the field of today's natural language processing.

- a) Problem Definition: Before the emergence of recurrent neural network RNN, researchers mostly studied text or speech signal data with FNN and N-gram language models. However, FNN can only process fixed-length text or signal due to the limitation of model structure,

and due to the uncertainty of the length of natural language text, FNN can not give enough spatial structure to process the text, and also FNN can not solve the sequential information of the model input.

- b) Research methods: In other words, the RNN model has the ability to "remember", it can capture the information that has been calculated before for the current calculation, the input sequence of x_{t-1}, x_t, x_{t+1} corresponds to the input of time $t-1, t, t+1$, o_{t-1}, o_t, o_{t+1} is the output of the corresponding sequence of x_{t-1}, x_t, x_{t+1} , o_{t-1}, o_t, o_{t+1} contains the sequence information before the current time, taking time t as an example, the output of $S_t = f(Ux_t + WS_{t-1})$, $o_t = g(VS_t)$, o_t contains the information of time t , and $f(\cdot)$ and $g(\cdot)$ are activation functions. Tasks that use RNNs as network structures typically include tasks with sequential information, such as Seq2Seq, named entity recognition, and text classification. The main mainstream machine learning based research methods are Long Short-Term Memory Networks (LSTM) and Gated Recurrent Units (GRU), both of which improve the structure of recurrent neural networks. LSTM alleviates the problem of gradient vanishing caused by the structure of RNN. GRU, on the other hand, improves on the computational complexity of LSTM.
- c) Long Short-Term Memory Network: LSTM is relative to the basic RNN with the addition of Cell state unit, which alleviates the problem of gradient vanishing caused by RNN processing of long text and random initialization of parameters of RNN at zero moment, and consists of input gate i , forgetting gate f , and output gate o . The formula for i, f, o is as follows:

$$f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f) \quad (4)$$

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i) \quad (5)$$

$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o) \quad (6)$$

where W, b is the weight matrix and deviation value, and σ is the activation function. cell C_t and hidden layer state h_t are calculated as follows:

$$\tilde{C}_t = \tanh(W_C \cdot [h_{t-1}, x_t] + b_c). \quad (7)$$

$$C_t = f_t * C_{t-1} + (1 - f_t) * \tilde{C}_t. \quad (8)$$

$$h_t = o_t * \tanh(C_t). \quad (9)$$

LSTM is the most widely used and successful recurrent neural network, which is widely used in industry and academia, although LSTM alleviates problems such as gradient vanishing, LSTM also has some problems such as computational complexity, GRU's for the problem of LSTM, modified on the network, its input gate, forgetting gate, and output gate into two gates of updating and reset gates, which reduces the model complexity, but the model accuracy does decrease.

In view of the above, in this paper, we will use LSTM network, and for the shortcomings of LSTM unidirectional network, use bidirectional LSTM network structure.

C. Migration learning and text segmentation

Migration learning is a branch of machine learning research, which contains two basic concepts: (1) domain, a set of instances and a collection of features or samples consisting of two parts, the feature space and the edge probability distribution. There are mainly two kinds of source and target domains, the source domain refers to the domain with a lot of labeled data and knowledge. The target domain is the domain to be labeled or tested. (2) Task, refers to the specific task which determines the goal of learning.

The specific principle of transfer learning is to use the source domain combined with certain methods to train a model with strong generalization, and then apply the model to the target domain for testing. The ultimate goal is to apply the knowledge from the source domain to the target domain and assist the target domain to build a robust model.

Migration learning is generally divided into four categories: sample-based migration learning, feature-based migration learning, model-based migration learning, and relationship-based migration learning. The sample-based migration learning method realizes migration by increasing the weight percentage of source data that is similar to the data distribution of the target domain to train the model. This method is easy to implement, the points to consider are sample screening and weight assignment, and can only be used if the source and target domain feature distributions are the same. Model-based migration learning method is to use the source domain data to train a model that can share parameters, and then make predictions on the target domain. Feature-based transfer learning is to transform the features of the two domains into a space so that their data distributions are the same, and then perform supervised learning normally. Relationship-based migration learning is training migration on similar relationships in the source and target domains.

Domain adaptive is a special migration learning technique, and its use scenario is generally used in the case where the distribution of the test set and the dataset is inconsistent, and the source domain data is small, and the related corpus to the target domain is small. Usually, there are three types of domain adaptation methods: one is model-based domain adaptation, which is mainly realized by redesigning the model, such as changing the architecture of the model, the loss function or the parameters of the model, and enhancing the feature space of the model. The second is data-based domain adaptation, which is realized by adjusting the data, including techniques such as pseudo-labeling, data selection and pre-training. The third one is a combination of the above two.

Text Segmentation (TS) refers to the process of extracting meaningful segment units from a text. According to the different contents of segmentation, text cutting tasks can be divided into four categories: word segmentation, phrase segmentation, sentence segmentation and topic segmentation. Word

segmentation is the process of splitting a string of text into its constituent words. Phrase segmentation is the task of dividing coherent text into key phrases. Sentence segmentation, on the other hand, takes the sentences in a text as the object of study and cuts them into basic linguistic units. Theme segmentation is the task of cutting the text will be divided into a number of consecutive themes based on the semantic information of the paragraph, which simply means that the paragraph is the center of the text.

III. Examples of Evaluation of Innovative Thinking in Secretarial Writing Practice

1) Analysis of model applications

Thirty-seven volunteers engaged in secretarial work were invited to participate in the study, firstly, they were divided into two categories: secretaries of public office-type affairs and secretaries of enterprise business affairs, and then the volunteers were divided into three groups of low level of innovation, medium level of innovation, and high level of innovation by mutual evaluation of each person's writing work, and then they were analyzed by using the innovative thinking scoring model of secretarial writing based on machine learning, in order to observe the role of innovative thinking in the secretarial writing practice and to verify the validity of the model.

Table 1 shows the calculation results of the model for the three groups of public service secretaries. It can be seen that the percentage of vocabulary innovation of the low, middle and high level groups of public service secretaries is 7.76%, 8.23% and 10.35% respectively, and the high level group has a higher percentage of using non-customary vocabulary that fits the development of the times and represents the emerging technologies and concepts in their secretarial writing than the two groups of middle and low level. As for the three groups of grammatical rhetoric and expressive techniques, the percentage of innovation is 2.21%, 3.89%, 17.65% and 7.98%, 10.19%, 16.46%, respectively, which can be seen that the high-level group uses rhetoric, diagrams, etc. in secretarial writing in a significantly higher proportion than the other two groups. As for the two innovative degrees of article structure and theme intention, the high level group is only about 1% higher than the other two groups, and the difference is not as obvious as that of grammatical rhetoric and expression skills. This is related to the work content of public service secretaries, who have less room for free play on the topic of secretarial writing.

Table 2 shows the results of the model's calculations for the commercial secretaries of the three groups of enterprises. It can be seen that the percentage of lexical innovation of the three groups of commercial secretaries in the low, medium and high groups are 10.29%, 21.53% and 27.74% respectively, and there is a significant gap between the three groups. The percentage of innovation of the three groups on grammar and rhetoric and article structure is 4.36%, 4.51%, 5.07% and 2.12%, 2.45%, 2.60% respectively, which can be seen that the three groups are less innovative in these two items, and

	Low level secretarial writing	Mid-level secretarial writing	High level secretarial writing
Vocabulary innovation proportion	7.76%	8.23%	10.35%
Grammatical rhetoric innovation proportion	2.21%	3.89%	17.65%
Article structure innovation proportion	5.77%	5.35%	7.82%
Presentation skill innovation proportion	7.98%	10.19%	16.46%
theme innovation proportion	4.16%	4.33%	5.20%

Table 1: The calculation of the secretary of public office

	Low level secretarial writing	Mid-level secretarial writing	High level secretarial writing
Vocabulary innovation proportion	10.29%	21.53%	27.74%
Grammatical rhetoric innovation proportion	4.36%	4.51%	5.07%
Article structure innovation proportion	2.12%	2.45%	2.60%
Presentation skill innovation proportion	12.38%	17.56%	36.87%
theme innovation proportion	9.32%	16.29%	29.75%

Table 2: The results of the enterprise business secretary's calculation

the gap between the high level group and the low level group is not more than 0.8%. The expression skills of the three groups are 12.38%, 17.56% and 36.87%, and the high-level group is much more than the remaining two groups, which shows that high-level corporate commercial secretaries use a lot of diagrams, animations and other forms of expression in their writing. The degree of innovation in theme intention was 9.32%, 16.29% and 29.75%, and the corporate commercial secretaries were more innovative in their choice of writing themes than the public service secretaries.

A. Model-assisted secretarial writing control trial

In order to verify whether the use of innovative thinking can actually improve secretarial writing, this paper designs a controlled experiment. The research subjects are office staff of government agencies, business secretaries of enterprises, administrative or teaching assistants of scientific research institutions and colleges, and secretariat staff of social welfare organizations, totaling 92 people. After starting the experiment, they are divided into experimental group and control group, and firstly, a pre-test is conducted to confirm whether the difference between the secretarial writing level of the two groups is significant or not, in order to ensure that the results of the experiment can be analyzed. Then a 10-week study of secretarial writing was conducted, and one secretarial writing practice topic was released to both groups every week. The topics were exactly the same for the experimental and control groups, but the experimental group was required to use modeling to enhance creative thinking skills and apply them to their subsequent writing. The experimental group was required to use the model to improve their creative thinking skills and apply them to their subsequent writing, and to improve their writing by analyzing the degree of creativity of their writing based on the model after completing each exercise. The control group was not allowed to use the model, and a post-test was conducted at the end of 10 weeks to check the effectiveness of the model.

At the end of the experiment, the data were collected and organized, and a comparison of the pre and post-test scores of the experimental group and the control group is shown in Table 3.

	Group	N	Mean	Standard deviation	T-Value	Sig.(Double tail)
Pre-survey	experimental group	45	15.74	3.562	-0.38	0.893
	control group	47	15.89	3.577		
Posttest	experimental group	45	18.09	3.296	2.613	0.014
	control group	47	16.13	3.418		

Table 3: The results of the experimental group and the control group

		Mean	N	Standard deviation	T-Value	Sig.(Double tail)
Control 1	Secretarial writing posttest score	16.13	47	3.418	0.612	0.591
	Secretarial writing premeasurement score	15.89	47	3.577		

Table 4: Contrast of the control group

From the Table 3, it can be seen that the mean scores of the experimental and control groups in the pre-test were 15.74 and 15.89 respectively, with standard deviations of 3.562 and 3.577, and a Sig value of 0.893, which did not reach a significant level. There was no significant difference in the pre-test scores between the two groups, and the level of secretarial writing was basically the same, which ensured the analyzability of the experiment. In the post-test scores, the average score of the experimental group is 18.09, and the score of the control group is 16.13, with a Sig value of 0.014, which is less than 0.05, and has reached a significant level, indicating that there is a significant gap between the two groups in the post-test. It can be assumed that the secretarial writing level of the staff in the experimental group has been significantly improved under the exercise of uninterrupted creative thinking exercises for 10 consecutive weeks.

Table 4 shows the comparison of the scores of the control group in the pre- and post-test. It can be seen that the Sig value of 0.591, which is greater than 0.05, did not reach the significant level, which further indicates that there was no significant difference in the performance of the control group before and after the 10-week test, and that there was no significant change in the level of secretarial writing.

Table 5 shows the pre and post-test scores of the experimental group as well as the changes in the individual scores. It can be seen that in the individual scores, vocabulary, grammar, structure, expression, and theme improved their scores by 0.47, 0.76, 0.35, 0.25, and 0.50 points respectively.

The Sig values of total writing score, vocabulary innovativeness score, grammar and rhetoric innovativeness score, and main idea innovativeness score are all 0.000, which is less than 0.05 and reaches the significant level. It indicates that the experimental group's performance is significantly different from the pre-test after 10 weeks of model-assisted learning. And the Sig values of the essay structure innovation degree score and the expression skill long Xindu score are 0.009 and 0.017, which are also less than 0.005 and reach the significant

		Mean	N	Standard deviation	T-Value	Sig.(Double tail)
Control 1	Secretarial writing posttest score	18.09	45	3.296	11.356	0.000
	Secretarial writing premeasurement score	15.74	45	3.562		
Control 2	Vocabulary innovation posttest	3.73	45	1.115	5.147	0.000
	Vocabulary innovation premeasurement	3.26	45	0.978		
Control 3	Grammatical rhetoric innovation posttest	4.52	45	0.852	7.263	0.000
	Grammatical rhetoric innovation premeasurement	3.76	45	0.879		
Control 4	Article structure innovation posttest	2.98	45	1.126	2.899	0.009
	Article structure innovation premeasurement	2.63	45	0.807		
Control 5	Presentation skill innovation posttest	4.11	45	0.889	2.573	0.017
	Presentation skill innovation premeasurement	3.86	45	0.912		
Control 6	theme innovation posttest	2.74	45	0.554	5.318	0.000
	theme innovation premeasurement	2.24	45	0.691		

Table 5: The total scores and individual results of the test group

level, and the changes are not as big as the remaining three, but the scores are also improved.

In summary, the results of analyzing the pre-test scores can be found that there is not much difference between the secretarial writing level of the two groups before the beginning of the study, which makes the study more objective and stable. And after 10 weeks of special training in writing using innovative thinking, the experimental group's writing scores increased substantially, and the effect of innovative thinking on secretarial writing level was significant. Among them, the effect on the degree of vocabulary innovation, grammatical innovation, and the degree of main idea innovation in secretarial writing is larger, while the effect on chapter structure and expression skills is smaller.

IV. Conclusion

This paper constructs an evaluation model of innovative thinking in secretarial writing based on machine learning related algorithms, uses the model to analyze the innovativeness of secretarial writing of 37 volunteers engaged in secretarial work, and finally conducts a controlled experiment on whether the use of innovative thinking can improve the level of secretarial writing, and draws the following conclusions:

- 1) The three groups of different levels of public service secretaries in the writing of grammatical rhetoric, expression skills innovation accounted for 2.21%, 3.89%, 17.65% and 7.98%, 10.19%, 16.46%, respectively, the high level group in the secretarial writing of the use of rhetoric, charts and graphs, etc., the proportion of the group is significantly higher than the other two groups. As for the two innovative degrees of article structure and theme intention, the high level group is only about 1% higher than the other two groups, with a lower degree of innovation.
- 2) The percentage of vocabulary innovation degree of commercial secretaries is 10.29%, 21.53% and 27.74%, with a significant gap among the three groups. The percentage of innovation in grammar and rhetoric and article structure is 4.36%, 4.51%, 5.07% and 2.12%, 2.45%, 2.60% respectively, and the overall innovation degree of commercial secretaries in these two items is low. Expression skills were 12.38%, 17.56%, and 36.87% for the three groups, with high-level corporate commercial secretaries making extensive use of graphs, animations, and other forms of expression in their writing. The degree of innovation in theme intention

is 9.32%, 16.29%, 29.75%, and corporate commercial secretaries are more innovative in thinking than public affairs secretaries in the selection of writing themes.

- 3) The average score of the experimental group in the post-test was 18.09, and the score of the control group was 16.13, with a Sig value of 0.014, which is less than 0.05, and there is a significant gap between the two groups' scores. In the course of 10 weeks of innovative thinking exercise, the secretary's innovation performance in the writing process has been significantly improved through the assistance of the machine learning model.

V. Recommendation

This study can also explore the theoretical basis of creative thinking in secretarial writing and its relationship with existing documents. In the sample selection and analysis method, it can further enhance its representation and universality. For example, adding more sample of secretarial categories and writing samples may make the findings more universal. In addition, the statistical analysis method of experimental data can be considered to introduce more modern statistical techniques to enhance the persuasion of research.

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References

- [1] Pons, A. (2018). El pasado fue analógico, el futuro es digital. Nuevas formas de escritura histórica. *Ayer*, (110), 19-50.
- [2] Wang, C., Ye, Q., & Goyal, A. (2019). Does tenure matter: role of the corporate secretary in Chinese-listed firms. *Accounting Horizons*, 33(1), 181-205.
- [3] Li, M., Chen, Y. T., Huang, C. Q., Hwang, G. J., & Cukurova, M. (2023). From motivational experience to creative writing: A motivational AR-based learning approach to promoting Chinese writing performance and positive writing behaviours. *Computers & Education*, 202, 104844.
- [4] Pouliot, V. (2020). Historical institutionalism meets practice theory: Renewing the selection process of the United Nations Secretary-General. *International Organization*, 74(4), 742-772.
- [5] Castro, P., & Santos, T. R. (2020). Dialogues with the absent Other: Using reported speech and the vocabulary of citizenship for contesting ecological laws and institutions. *Discourse & Society*, 31(3), 249-267.
- [6] Ravndal, E. J. (2020). A guardian of the UN charter: The UN secretary-general at seventy-five. *Ethics & International Affairs*, 34(3), 297-304.
- [7] Su, Y. S., Lin, C. L., Chen, S. Y., & Lai, C. F. (2020). Bibliometric study of social network analysis literature. *Library hi Tech*, 38(2), 420-433.
- [8] De Vivo, F. (2019). Microhistories of long-distance information: space, movement and agency in the early modern news. *Past & Present*, 242(Supplement_14), 179-214.
- [9] Zhang, M. (2022). Variation in metadiscourse across speech and writing: A multidimensional study. *Applied Linguistics*, 43(5), 912-933.
- [10] García-Avilés, J. A. (2021). Journalism innovation research, a diverse and flourishing field (2000-2020). *Profesional de la Información*, 30(1).
- [11] Wahyuni, S. (2018). The effect of blended learning model towards students' writing ability. *J-SHMC: Journal of English for Academic*, 5(2), 97-111.
- [12] Alpern, S., & Baston, V. (2017). The secretary problem with a selection committee: do conformist committees hire better secretaries?. *Management Science*, 63(4), 1184-1197.
- [13] Granado-Peinado, M., & Huertas, J. A. (2023). A Teaching Innovation Project on Writing Critical Essays in a History of Psychology Course. *Teaching of Psychology*, 50(3), 284-290.

- [14] Barczak, G. (2017). Writing a review article. *Journal of Product Innovation Management*, 34(2).
- [15] Limpo, T., & Alves, R. A. (2017). Written language bursts mediate the relationship between transcription skills and writing performance. *Written Communication*, 34(3), 306-332.
- [16] Ober, T. M. (2021). The Use of a Digital Pedagogical Tool to Support Writing Instruction in the Social Sciences. *Teaching of Psychology*, 48(4), 300-307.
- [17] Matsumoto, Y. (2019). Material moments: Teacher and student use of materials in multilingual writing classroom interactions. *The Modern Language Journal*, 103(1), 179-204.
- [18] Goode, C. T., Lamoreaux, M., Atchison, K. J., Jeffress, E. C., Lynch, H. L., & Sheehan, E. (2018). Quantitative skills, critical thinking, and writing mechanics in blended versus face-to-face versions of a research methods and statistics course. *Teaching of Psychology*, 45(2), 124-131.

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