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A Study on Enhancing Brand Recognition in the Housing Market through Advertising Creativity in the New Liberal Arts Era

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Abstract The optimization of keyword generation, expansion and selection in housing brand advertisement creativity has a role to play in the enhancement of brand awareness in the housing market that should not be taken lightly. In this paper, a generative pretraining model (ProphetNet) containing a future prediction mechanism is used as a prediction method for advertising keywords, which effectively enhances the model's understanding of the context and the coherence of the generated text by predicting multiple future words. After obtaining multiple ad creative keywords, the hierarchical Bayesian model is used to summarize the prior information of ad keywords based on historical data and experience. And the parameter estimation between the ad creative keywords and the brand recognition in the housing market is performed to generate the final keywords. The designed ProphetNet model consistently stabilizes the average accuracy at 0.6 and above under a variety of keyword expansion numbers, which is both effective and stable.

Index Terms hierarchical Bayesian modeling, generative pretraining model, brand awareness, future prediction mechanism, advertising creativity

I. Introduction

In today's competitive housing market, brand recognition is critical to the success of housing brands [1], [2]. A brand that is widely recognized and acknowledged by consumers is often able to stand out in a panoply of competitors and win more market share and customer loyalty [3], [4]. And advertising creativity, as an important means of brand communication, has an indispensable role in improving housing brand awareness [5].

First of all, advertising creativity can attract consumers' attention. In the era of information explosion, consumers are exposed to a large amount of advertising information every day, if the advertising creativity is bland and lacks novelty, it is easy to be ignored by consumers [6]-[8]. And a housing brand advertisement with unique creativity can quickly catch consumers' eyes and arouse their interest and attention among many advertisements [9], [10]. Secondly, advertising creativity can clearly convey the core value and personality of the brand [11]. The core value of the brand is the soul of the housing brand, and the advertising creative is an important bridge to convey the core value of the brand to consumers [12], [13]. An excellent advertising idea can show the core value and personality of the brand in a vivid and graphic way, so that consumers have a clear and deep understanding of the brand in a short time [14]-[16].

Furthermore, advertising creativity can stimulate the emotional resonance of consumers [17]. When consumers buy products or services, not only based on rational needs, but more often influenced by emotional factors [18], [19]. An advertising creative that can touch the deepest emotions of consumers can enable consumers to establish an emotional connection with the brand and enhance the sense of identity and loyalty to the brand [20], [21]. In addition, advertising creativity can also create a unique brand image and memory points, and an advertising creativity with distinctive features and unique memory points can leave a deep impression of the brand in the minds of consumers [22], [23].

In this paper, we first describe in detail the core future prediction mechanism construction and operation steps based on the structural design of ProphetNet. After obtaining the advertising keywords of different brands in the housing market using the ProphetNet model, a hierarchical Bayesian model is introduced to explain the implementation process of model parameter estimation and the necessary conditions for its operation. Then, the experiments on the prediction accuracy of the ProphetNet model are carried out in the form of comparing similar modeling methods, and the effects of different numbers of keyword extensions on the performance of the model are explored. Finally, based on the ProphetNet model and the hierarchical Bayesian model, the keyword selection strategy is explored to investigate the transmission relationship between advertisement creativity and brand awareness enhancement.

II. Selection of keywords for advertising creativity

II. A.ProphetNet model structure

In this paper, we propose a new sequence-to-sequence generative pretraining model, called ProphetNet, which is based on the Transformer encoder-decoder architecture. Compared with the original model, ProphetNet introduces four modifications: (1) A novel self-supervised goal for future multi-word meta-prediction. (2) Multi-stream self-attention mechanism. (3) Positional embedding modification. (4) Mask-based sequence-to-sequence pretraining for the self-encoder denoising task. Figure 1 shows the architecture of ProphetNet.

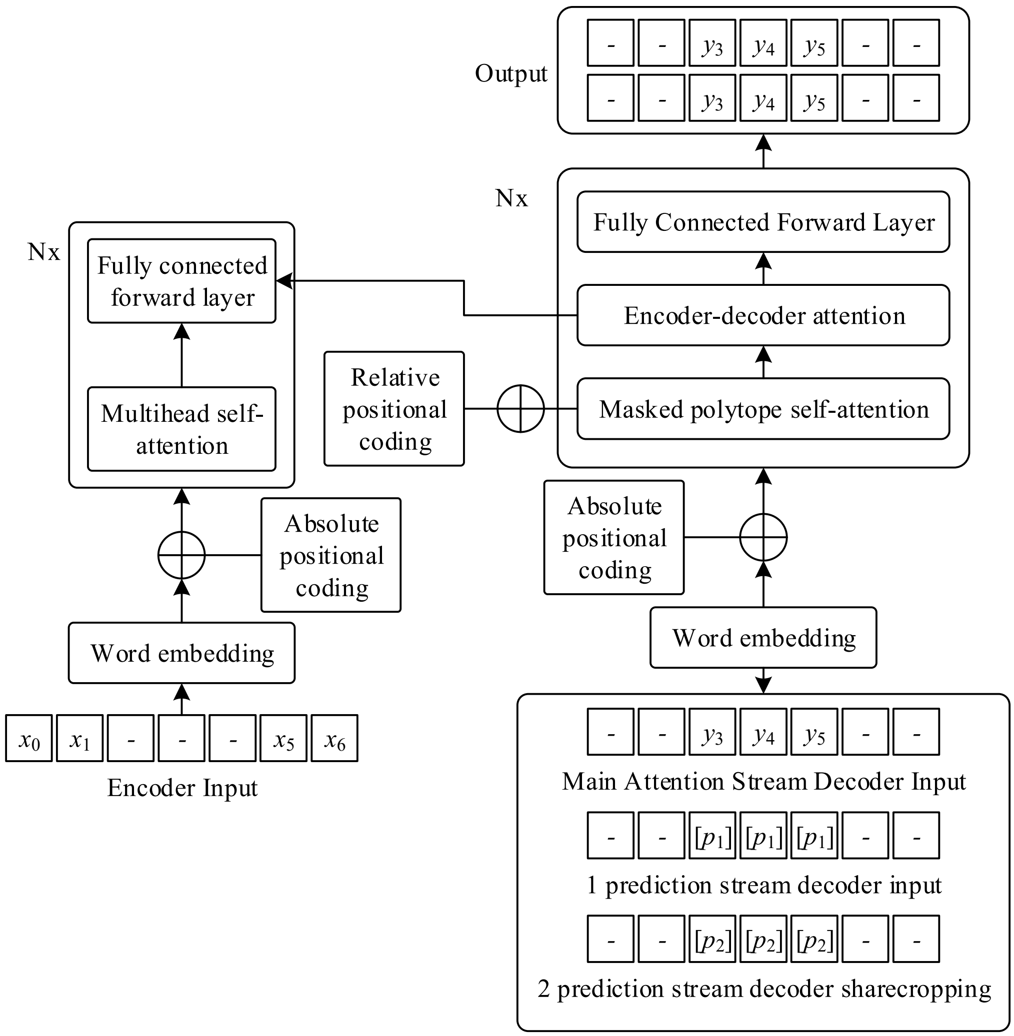

Figure 1: The structure of the ProphetNet pre-trained model

The description of future multi-word element (n-gram) prediction is developed next.

Consider the workflow of a standard Transformer encoder-decoder, for a given input sequence as in equation (1):

$$X = (x_0, x_1, \ldots x_M) \quad (1)$$

Model it and output the sequence as in equation (2):

$$Y = (y_0, y_1, \ldots y_N) \quad (2)$$

The standard Transformer uses an autoregressive modeling approach, i.e., for the prediction of each target lexeme y_t, using the input sequence X and the previous information $y_{<t}$, the probability of generating each lexeme is computed over the entire target lexicon and the lexeme with the highest confidence is selected as the prediction result, which is generated word by word to obtain the final complete sequence.

Although the conditional probability used by the decoder to predict the lexical element y_t is $p(y_t \mid X, y_{<t})$, in fact the antecedent information of $y_{<t}$ is not equally important. If the prediction of y_t is initialized using y_{t-1}, it will lead to a strong dependence of y_t on y_{t-1}, while in this paper, we hope that the antecedent information can be utilized more fully during pre-training so as to alleviate the strong dependence on the immediately adjacent lexical elements. In addition, this paper hopes that more future information can be included in the hidden state of the preceding text obtained by pre-training, so as to enhance the global view and expressive ability of the model. Finally, this paper also hopes to introduce the auxiliary task of predicting multiple future lexical elements in parallel and simultaneously at pre-training given the preceding information. For the processing of unlabeled natural language text, in order to construct input-output matching pair one for training, this paper then deletes a segment of consecutive characters in the pre-training text, and the remaining portion is used as the input sequence X, and the deleted portion is used as the prediction sequence Y, in order to serve as a self-supervised task for the language model.The training objective of ProphetNet replaces $p(y_t \mid x, y_{<t})$ be replaced by $P(y_{t:t+n-1} \mid x, y_{<t})$, to predict subsequent n lexical elements given the antecedent, and to design model structures that can simultaneously predict future n lexical elements. The model structure adopted for the example that $n=2$ can predict the next two words simultaneously each time is shown in Schematic 1.

First, as shown on the left side of Schematic 1, the input x sequence is encoded as the hidden state $H_{enc} = Encoder(x_0, x_1, \ldots x_M)$, which is the same structure as the original Transformer encoder here. The decoder on the right hand side, on the other hand, simultaneously predicts the distribution probabilities of the next n lexical elements as in equation (3):

$$p(y_t \mid x, y_{<t}), \ldots, p(y_{t+n-1} \mid x, y_{<t}) = Decoder(y_{<t}, H_{enc}) \tag{3}$$

The final loss function can be expressed as equation (4):

$$\begin{aligned} \mathrm{L} &= -\sum_{n=0}^{N-1} \alpha_n \cdot \left(\sum_{t=1}^{T-n} \log p_\theta (y_{t+n} \mid y_{<t}, x) \right) = \underbrace{-\alpha_0 \cdot \left(\sum_{t=1}^{T} \log p_\theta (y_t \mid y_{<t}, x) \right)}_{\text{Language Modelling Loss}} \\ & \underbrace{-\sum_{n=1}^{N-1} \alpha_n \cdot \left(\sum_{t=1}^{T-n} \log p_\theta (y_{t+n} \mid y_{<t}, x) \right)}_{\text{Future multi-word element loss (n-gram loss)}} \end{aligned} \tag{4}$$

The above future multi-word meta-prediction goal can be seen to consist of the following two components:

(1) A conditional language modeling loss identical to that forced by the original teacher.

(2) An $n-1$ future lexical element prediction loss that forces the model to predict future target lexical elements. The future multi-word element prediction loss explicitly encourages the model to plan for future word element predictions and prevents overfitting on strong local correlations. In addition, this paper assigns a different weight α_j to each loss as a trade-off between traditional language modeling and future $n-gram$ prediction. Another alternative strategy is to give higher weights to word element predictions that are closer to the future, which is similar to the discount factor for future rewards in reinforcement learning.

II. B.Bayesian parameter estimation

Operationally, it is possible to estimate the probability of importance of each section on a sample corpus of advertisement keywords. A sample corpus of housing market brands can be constructed by utilizing the textual link structure of the advertisement comment section. The sample corpus contains pages with entries titled with the seed keyword as well as pages with link paths to that page, and a set of pages will be randomly selected from the corpus as an estimation sample. According to a general inference, the topic word of the page (i.e., the title keyword) should appear in the significant part of the page. Therefore, in order to determine the importance of each section of the page, the importance of each section can be back extrapolated by the frequency statistics of the occurrence of the page's topic words in each section.

Bayesian model parameter estimation typically requires that the model satisfy several basic conditions:

(1) The stochastic model contains a single unknown parameter.

(2) The prior information about the unknown parameter is chi-square (meaning a set of information consisting of similar components) and deterministic.

(3) The observed data are chi-square and deterministic.

A chi-subtotal implies that each individual is of the same type, and several sections presented on the same page fit this profile. The procedure for Bayesian parameter estimation of the probability of importance of each section is as follows: for each sample page, it is necessary to determine the occurrence of its title keyword in each section. For each section, x_j is recorded as the total number of times the title keyword does not appear in it, which can be assumed to conform to a Poisson distribution. This is because the Poisson distribution is often used to describe the number of occurrences of random events per unit of time (or space), such as the number of failures of a system's work units for a certain period of time, the number of people using a certain device for a certain period of time, the number of failures of a machine, and so on. The following basic conditions are assumed for Poisson distribution:

(1) The probability of two events occurring simultaneously within a short time frame is approximately equal to zero.

(2) The probability of an event occurring within a small time period is proportional to the length of the time period.

(3) An event that occurs within one time frame does not affect the probability of an event that occurs within another non-overlapping time frame.

The parameter λ of the Poisson distribution is the average number of occurrences of a random event per unit of time (or per unit of area), and the observed data is the number of events that occur in a given time period, in the form of the data shown in Fig. 2. Here it is the total number of times that the title keyword does not appear in a given section x_j.

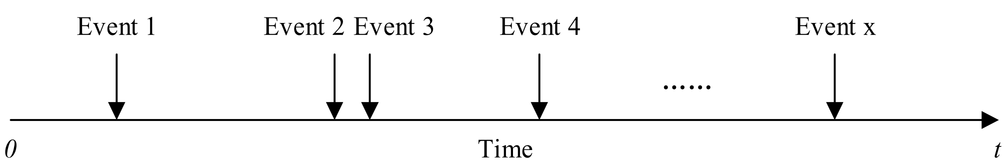

Figure 2: The manifestation of Poisson distribution events on the time axis

Set θ_j as a random variable obeying a Beta distribution, i.e., $\theta_j \sim B(\alpha'_j,\beta'_j)$, $\theta_j = 1-\alpha_j$. In this process, θ_j and its parameters (i.e., α'_j,β'_j) are estimated from the sample data x_j.

Assuming that θ_j, α'_j, and β'_j are independent in the conditional probability distribution of a given x_j, a plain Bayesian model is used here to derive the conditional probability distribution from the posterior joint distribution $p(\theta_j,\alpha'_j,\beta'_j \mid x_j)$, to obtain θ_j and its parameters α'_j and β'_j, which are the three random variables of the sample data x_j given the sample data x_j (i.e. $\theta_j,\alpha'_j,\beta'_j$) of the joint distribution. According to Bayes' theorem, $p(\theta_j,\alpha'_j,\beta'_j \mid x_j)$) can be obtained by equation (5).

$$\begin{aligned} p(\theta_j,\alpha'_j,\beta'_j \mid x_j) &= \frac{p(x_j \mid \theta_j,\alpha'_j,\beta'_j)\,p(\theta_j,\alpha'_j,\beta'_j)}{p(x_j)} \\ &= \frac{p(x_j \mid \theta_j,\alpha'_j,\beta'_j)\,p(\theta_j \mid \alpha'_j,\beta'_j)\,p(\alpha'_j,\beta'_j)}{p(x_j)} \\ &\propto p(x_j \mid \theta_j,\alpha'_j,\beta'_j)\,p(\theta_j \mid \alpha'_j,\beta'_j)\,p(\alpha'_j)\,p(\beta'_j) \end{aligned} \tag{5}$$

where $p(x_j \mid \theta_j,\alpha'_j,\beta'_j)$ is the probability of x_j given the prior of θ_j, α'_j and β'_j. Conditional prior $p(\theta_j \mid \alpha'_j,\beta'_j)$ is the prior of θ_j given the prior of α'_j and β'_j, i.e., when α'_j and β'_j can be determined. $\theta_j \sim B(\alpha'_j,\beta'_j)$ $p\left(\alpha'_j\right)$ and $p\left(\beta'_j\right)$ are the prior probabilities of α'_j and β'_j, respectively.

Based on Eq. (5), the posterior joint probability distribution $p(\theta_j,\alpha'_j,\beta'_j \mid x_j)$ can be estimated by means of a hierarchical model containing the following stages.

The first stage is to determine α'_j and β'_j. Considering that α'_j and β'_j are parameters of the Beta distribution of θ_j, the Gamma distribution is taken as its superprior ($\alpha'_j \sim \Gamma(\delta,\tau)$, $\beta'_j \sim \Gamma(\delta,\tau)$). Due to the lack of a priori information, the hyperparameters (δ,τ) of α'_j and β'_j are set to be constants, i.e., $\delta = 15$ and $\tau = 20$, for this study.

The second stage is to determine the conditional prior $p(\theta_j \mid \alpha'_j, \beta'_j)$. With the prior of α'_j and β'_j already determined after the completion of the first stage, Markov chain Monte Carlo (MCMC) simulations are applied to obtain $p(\theta_j \mid \alpha'_j, \beta'_j)$. The MCMC method is based on approximating the plotted values of θ_j in the distribution and then correcting these plots to better approximate the distribution of θ_j. The plots are taken sequentially, and then all the plots form a Markov chain, i.e., a series of random variables $\theta_j^1, \theta_j^2, \cdots, \theta_j^t$. For any t, the distribution of θ_j^t given all previous θ_j depends only on the most recent value θ_j^{t-1}. The MCMC method can approximate the approximate distribution step by step through each step of the simulation. Thus, with enough repetitions, it will gradually converge to approximate the actual distribution of θ_j.

The third stage is to determine $p(x_j \mid \theta_j, I)$. I is the number of title keywords in the estimated sample. The structure of the Bayesian hierarchical model is shown in Fig. 3, according to the hierarchical relationship in Fig. 3, x_j depends on α'_j and β'_j through θ_j, so $p(x_j \mid \theta_j, \alpha'_j, \beta'_j)$ will have, θ_j, α'_j and β'_j as its priors. In the previous section, $x_j \sim Poisson(\mu_j)$ has been set, where the parameter μ_j is the average number of times the headline keyword has not appeared, which can be obtained by $\mu_j = \theta_j \times I$. As in the second stage, $p(x_j \mid \theta_j, \alpha'_j, \beta'_j)$ can be obtained by simulation with the MCMC method.

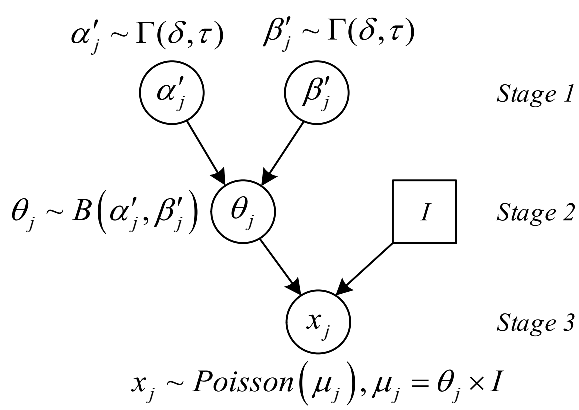

Figure 3: Bayesian hierarchical model structure

The weight of each keyword extracted from the pages in the corpus is then used to calculate the weight of the keyword. Finally a set of keywords can be generated by ranking the keywords based on their weights.

III. Performance Evaluation and Application of Keyword Selection Models

III. A. Overall performance analysis of the model

III. A. 1) Accuracy

Four traditional keyword extraction methods: (M1) Baseline-B1, (M2) SmallWord-SW2, (M3) WordTracker-WT3, and (M4) SeparatingModel-SM4 are chosen as the comparison methods, and 1000 data are randomly extracted for language model mining, and compared with the (M5) model of this paper. Algorithm's accuracy performance in 5 iterations. Figure 4 depicts the experimental results of the five modeling algorithms after five iterations, and it can be seen that (M5)This paper's modeling algorithm consistently maintains the highest accuracy among the five modeling algorithms, and the overall performance is significantly improved with the increase in the number of iterations, from 0.35 in the first iteration to 0.42 in the fifth iteration.

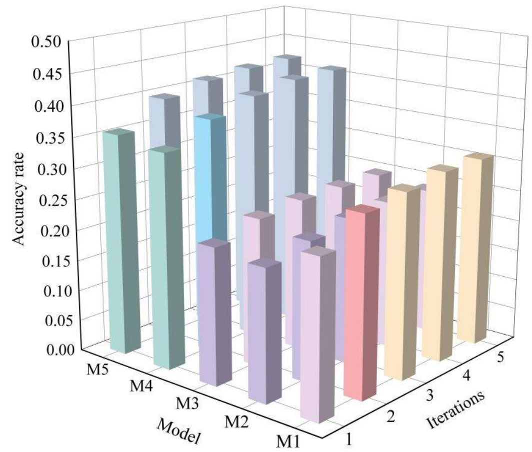

Figure 4: Experiment on the Number of Iterations of Keyword Extraction Algorithm

MiFi, MaFi, MiP, MiR, MaR, and MaP are selected as the experimental dataset, and the results of the comparative experiments of advertisement keyword extraction for unfolding five modeling algorithms are shown in Table 1. Among them, the (M5) modeling algorithm in this paper performs much better than its counterparts on all the other five datasets except for the Map dataset where it slightly loses performance to the (M1) Baseline-B1 modeling algorithm and achieves an optimal performance of 0.59 on MiFi.

Table 1: Comparative experiment on Advertising Keyword extraction

Model	MiFi	MaFi	MiP	MiR	MaR	MaP
M1	0.54	0.39	0.53	0.39	0.44	0.48
M2	0.53	0.4	0.52	0.4	0.45	0.45
M3	0.55	0.4	0.52	0.4	0.45	0.45
M4	0.57	0.41	0.56	0.41	0.47	0.46
M5	0.59	0.42	0.58	0.41	0.48	0.47

III. A. 2) Effect of different number of keyword extensions on model performance

The (M3) WordTracker-WT3 and (M4) SeparatingModel-SM4 modeling algorithms, which perform better in the above experiments, are selected to further develop the comparative analysis with (M5) modeling algorithm of this paper in terms of the impact of different number of keyword extensions on performance. Figure 5 shows the performance of the three modeling approaches regarding the average accuracy at different numbers of keyword extensions. It can be seen that the number of keywords has a certain effect on the performance of the model algorithm. As the number of keyword extensions increases, the average accuracy of the three algorithms decreases to different degrees. However, (M5) the modeling algorithm in this paper is always higher than the other two algorithms in the overall average accuracy, and when the number of keywords reaches 200, the average accuracy can still be maintained at 0.6 and above, with better performance.

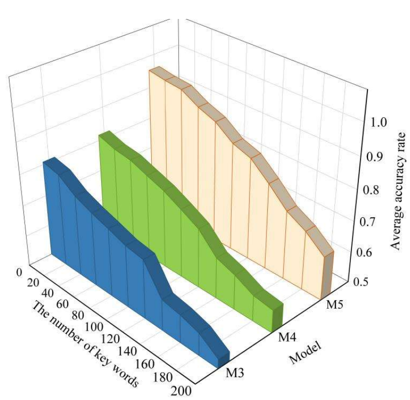

Figure 5: The performance of algorithms under different keywords

III. B. Test of mediating role of keywords

The mediating variable is the variable that acts between the independent variable and the dependent variable, which not only describes the mechanism of the independent variable's action on the dependent variable, but also describes the relationship between the variable and the dependent variable as well as the muscle of the action. In this section, the (*kw*) keywords generated by ProherNet model and hierarchical Bayesian model are selected as mediating variables, and the types of advertising creativity are briefly categorized into the following three types:(T1) product/service-oriented, (T2) emotion-oriented, and (T3) entertainment-oriented, and then the effects of brand awareness enhancement in the housing market are classified into (E1) awareness enhancement, (E2) audience increase,. Finally, different types of advertising creative are put in different models to verify the mediating role of keywords in each dimension.

Here, based on the research needs, this paper proposes the following research hypotheses:

H1: Product/service-oriented advertising creativity positively influences brand awareness in the housing market.

H2: Product/service-oriented advertising creativity has a positive impact on the increase of brand audience in the housing market.

H3: Emotionally oriented advertising creativity positively influences the increase of brand awareness in the housing market.

H4: Emotionally oriented advertising creativity positively influences the increase of brand audience in the housing market.

H5: Entertainment-oriented advertising creativity has a positive impact on the increase of brand awareness in the housing market.

H6: Entertainment-oriented advertising creativity has a positive impact on the increase of brand audience in the housing market.

III. B. 1) Product/service-based advertising creativity and brand recognition

In order to test whether keywords play a mediating role in the impact of product/service-oriented advertising creativity on brand awareness in the housing market, this study is analyzed in two models. First, only two variables of product/service-oriented advertising creativity on brand awareness enhancement are introduced (Model 1) and the relationship between them is examined. In Model 2, keywords are introduced to verify its mediating role, as well as to explore the mediating role it plays in it (partial/full mediation), so as to explore the mediating role of keywords between the effects of product/service-oriented advertising creativity on brand awareness in the housing market.

The relationship between the mediating role of keywords in product/service-oriented advertising creativity and brand awareness in the housing market is shown in Table 2.

Table 2: The role of key words between T2 and the enhancement of brand awareness

	Model 1 (No Mediation)		Model 2 (Keywords as mediators)	
	β value	*t* value	β value	*t* value
H1→E1	0.68	11.259	0.365	5.724
H2→E2	0.618	9.582	0.317	4.159
T1→*kw*			0.619	9.619
kw→E1			0.758	14.832
kw→E2			0.73	12.754

In Model 1, product/service-oriented advertising creativity significantly affects the increase of brand awareness in the housing market (β=0.68, t=11.259>1.96), and the increase of audience (β=0.618, t=9.582>1.96), which supports that hypotheses H1 and H2 are valid. In Model 2, the variable of keywords is introduced, and according to the test of mediating role, the path system of product/service-oriented advertisement creativity to keywords is significant (β=0.619, t=9.619>1.96). It indicates that the choice of keywords plays a partial mediating role in the design of product/service-oriented advertisement creative and the increase of brand awareness (β=0.758, t=14.832>1.96) and the increase of audience (β=0.73, t=12.754>1.96), respectively.

III. B. 2) Emotionally oriented advertising creativity and brand recognition

The mediating role of keywords in the relationship between emotionally oriented advertising creativity and brand awareness in the housing market is shown in Table 3, which is constructed in the same way as in the previous subsection for Model 1 and Model 2.

Table 3: The role of key words between T2 and the enhancement of brand awareness

	Model 1 (No Mediation)		Model 2 (Keywords as mediators)	
	β value	*t* value	β value	*t* value
H3→E1	0.685	0.422	0.34	4.916
H4→E2	0.643	0.243	0.32	4.092
T2→*kw*			0.665	10.846
kw→E1			0.76	14.214
kw→E2			0.719	12.12

In Model 1, there is no significant relationship between emotionally oriented advertising creativity in influencing the increase in brand awareness of brand perception in the housing market (β=0.685, t=0.422<1.96), and the increase in audience (β=0.643, t=0.243<1.96), which does not support the hypotheses H3 and H4 to hold. While in model 2, the variable of keywords is introduced, according to the test of mediating role, the path system of emotion-oriented advertising creativity to keywords is significant (β=0.665, t=10.846>1.96). It indicates that purely emotion-oriented advertising creativity does not positively assist the increase of brand awareness in the housing market, while the choice of keywords plays a partial mediating role in the design of product/service-oriented advertising creativity and the increase of brand awareness (β=0.76, t=14.214>1.96) and the increase of audience (β=0.719, t=12.12>1.96), respectively. Therefore, in the development of creative programs for brand advertising in the housing market, it is recommended to avoid emotionally oriented types of themes if there is no guidance based on the keywords given in the model.

III. B. 3) Entertainment-oriented advertising creativity and brand recognition

The relationship between the mediating role of keywords in the relationship between entertainment-oriented advertising creativity and brand awareness in the housing market is shown in Table 4.

Table 4: The role of key words between T3 and the enhancement of brand awareness

	Model 1 (No Mediation)		Model 2 (Keywords as mediators)	
	β value	t value	β value	t value
H5→E1	0.584	8.76	0.26	3.229
H6→E2	0.612	9.438	0.327	4.459
T2→kw			0.593	8.966
kw→E1			0.814	25.802
kw→E2			0.73	13.029

In Model 1, entertainment-oriented advertising creative significantly affects the increase of brand awareness (β=0.584, t=8.76>1.96) and the increase of audience (β=0.612, t=9.438>1.96) in the housing market, which supports the hypotheses H5 and H6 are valid. In Model 2, the variable of keywords was introduced, and according to the test of mediating role, entertainment-oriented advertising creative design played a fully mediating role with the increase of brand awareness (β=0.814, t=25.802>1.96), and the increase of audience (β=0.73, t=13.029>1.96). Therefore, in the selection of creative themes for brand advertising in the housing market and the design of program content, keywords and entertainment-oriented themes should be fully integrated to promote brand awareness in the housing market.

IV. Conclusion

The main findings of this paper are as follows:

(1) Based on the Trasformer encoder-decoder architecture, a future prediction mechanism is added to the traditional generation training model to improve the natural language generation effect of the model. The PropherNet model is established as a keyword prediction method for brand advertising creative in the housing market. The Hierarchical Bayesian model is used to develop the parameter estimation between the keywords of advertisement creativity and the brand awareness enhancement of housing market, and to generate the final keywords. Compared with similar modeling algorithms, the PropherNet model is able to achieve the highest accuracy of 0.42 at the 5th iteration, and consistently maintains an accuracy of 0.6 and above with different numbers of keyword extensions.

(2) The keywords identified by the fusion of the PropheNet model and the hierarchical Bayesian model were used as mediator variables to explore their mediating roles in the relationship between different oriented advertising ideas and brand awareness in the housing market. After the introduction of the keyword mediator variable, the product/service-oriented advertising creativity and the increase of brand awareness and audience are:

β=0.758, t=14.832>1.96, β=0.73, t=12.754>1.96, respectively; the emotion-oriented advertising creativity and the increase of brand awareness and audience are: β=0.76, t=14.214 >1.96, and β=0.719, t=12.12>1.96, with the keyword variable playing a partial mediating role. Whereas, entertainment-oriented advertising creativity with with the increase in brand awareness and the increase in audience were β=0.814, t=25.802>1.96, and β=0.73, t=13.029>1.96, respectively, which played a fully mediating role.

Accordingly, this paper suggests that in the design and development strategy of advertising creative programs for housing market brands, the PropherNet model and hierarchical Bayesian model should be used to identify keywords and use them as the basis for designing advertising programs that meet the market demand with entertainment-oriented as the main direction of development, so as to promote the enhancement of brand awareness in the housing market.

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