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RESEARCH ARTICLE

Detecting Novelty Seeking From Online Travel Reviews: A Deep Learning Approach

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ABSTRACT Travel online reviews is important experience related information for understanding an inherent personality trait, novelty seeking (NS), which influences tourism motivation and the choice of tourism destinations. Manual classification of these reviews is challenging due to their high volume and unstructured nature. This paper aims to develop a classification framework and deep learning model to overcome these limitations. A multi-dimensional classification framework was created for NS personality trait that includes four dimensions synthesized from prior literature: relaxation seeking, experience seeking, arousal seeking and boredom alleviation. Based on 30 000 reviews from TripAdvisor we propose a deep learning model using Bidirectional Encoder Representations from Transformers (BERT)- Bidirectional Gated Recurrent Unit (BiGRU) to recognize NS automatically from the reviews. The classifier based on BERT- BiGRU and NS multi-dimensional scales achieved precision and F1 scores of 93.4% and 93.3% respectively, showing that NS personality trait can be relatively accurately recognized. This study also demonstrates that the classifier based on multi-dimensional NS scales can produce satisfactory results using the deep learning model. The findings also indicate that the BERT- BiGRU model achieves the best effect compared to the same kind of deep learning models. Moreover, it proves that personality traits can be automatically identified from travel reviews based on computational techniques. For practical purposes, this study provides a comprehensive classification framework for NS, which can be used in marketing and recommendation systems operating in the tourism industry.

INDEX TERMS Tourism industry, BERT- BiGRU, novelty seeking, online travel reviews.

I. INTRODUCTION

With the rapid development of information technology, the internet has gradually penetrated many areas of our daily lives. The tourism industry has gradually extended from offline to online. With the emergence of online travel communities, a rapidly increasing number of tourists search the internet for destination introductions and comments about travel experiences from other travelers before making travel decisions [1].

Most online tourism platform reviews reflect what tourists see, feel, and think. Suppose this information is collected and analyzed to visually reveal tourists' praise and criticism attitudes or emotional tendencies about the elements of tourism services. In that case, it will help tourists understand the emotional tendencies of the forerunners towards a certain tourist destination and support tourists in their decision-making [2]. Tour operators can understand tourists' opinions or their attitudes of praise and criticism to maximize their strengths and avoid weaknesses. Reviews also help managers customize products or improve programs and gain a competitive advantage [3].

Personality traits are a group of psychological structures that trigger individual behavior and make individuals respond in the same way to different kinds of stimuli [4]. Traditionally, researchers use self-reporting scales to collect data on personality traits, which requires subjects to self-evaluate their personality traits following the actual situation [5]. Because

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the personality trait measurement scale mainly relies on the subjects' subjective feelings and self-statement, most personality trait measurement scales are currently standardized tests [6].

However, individuals responding to surveys are prone to expressing themselves more in line with social values and more conducive to self-representation. In other words, participants can deliberately submit distorted responses, which negatively affects the efficacy of measurement results [7].

Compared with the measurement of personality traits by psychological tests, personality trait recognition based on online behavior data is a method to automatically recognize and judge personality trait types [8]. On the one hand, it overcomes the subjective and static nature of traditional personality trait measurement methods. On the other hand, it also avoids the measurement bias caused by self-reporting and provides new methods and ideas for tourists' personality traits acquisition.

Novelty seeking (NS) is a personality trait [9], manifested as a general tendency to pursue diversification, curiosity, complexity, and strong feelings and experiences. NS is known to be an important motive for pleasure tourism and is considered an inherent quality [10], [11]. It has been proven to play an inseparable role in the choice of destination and has been one of the greatest impact factors on tourists' perceptions [12]. Previous research has shown that NS affects tourists' return intention [13], destination loyalty [14], and satisfaction [15].

NS is a personality trait widely recognized as an influencer of tourism motivation and plays a crucial role in formulating marketing strategies for the tourism industry. Since NS people like to go to remote and unfamiliar places, in the field of personalized recommendation, new tourist destinations can be recommended according to customers' NS tendencies. In addition to developing better recommender systems, organizations can also design more targeted marketing campaigns based on customer needs. It may help improve tourist satisfaction, reduce information duplication and diversify recommendations.

From a practical point of view, through NS identification in online travel reviews, user groups with NS characteristics can be accurately identified and located. However, due to the increasing amount of information in tourism online reviews, identifying tourists' NS characteristics is a difficult task. Manually analyzing a large number of online reviews is a time-consuming and costly method for identifying NS. To address this issue, this study attempts to introduce deep learning methods. After developing a multidimensional NS scale, we apply deep learning named BERT-BiGRU model to detect and classify NS in online travel reviews.

In the next section, this study reviews the relevant literature. Then, a deep learning-based NS recognition model was developed and tested. Finally, the application of the model is discussed. This study also discusses implications for future research and practice.

II. LITERATURE REVIEW

This section introduces the related literature reviews including text classification based on deep learning, personality trait recognition and novelty seeking. Through combing and analyzing relevant literatures, it is found that BERT- BiGRU model is appropriate to recognize NS personality trait.

A. TEXT CLASSIFICATION BASED ON DEEP LEARNING

Text classification is an important component in natural language processing (NLP) [16]. The probability and distribution information of each word in the document was used to estimate the importance of each word in the text classification based on the idea of probability statistics [17]. Traditional methods show the limitations of poor performance on multi-classification tasks [18]. In order to deal with new data trends, more effective text classification methods are needed. The Bayesian principle for text classification was proposed first [19].

Researchers realized that deep learning methods could significantly improve classification results [20]. This improvement is attributed to many factors, including the leap in computing power brought by hardware advancements, massive training data, efficient information system management and flexibility to learn intermediate representations [21], [22], [23].

The mainstream deep learning models currently used for text classification tasks include Convolutional Neural Networks (CNN) [24] and Recurrent Neural Network (RNN) [25]. CNN was proposed for text classification and achieved excellent results on trained word vectors [24]. In terms of RNN, variants of RNN-based models Long Short-Term Memory (LSTM) [26] and Gated Recurrent Unit (GRU) [27] are commonly used.

LSTM text sentiment classification model was proposed based on the RNN text classification model [26]. Based on the idea of feature fusion and fuses, the external features of words in the LSTM model enrich the text features and improve the performance of the model [25]. The BiLSTM model was proposed to accurately distinguish between personality traits and explicit emotions [27]. In recent 10 years, with the development of large-scale deep neural network technology, deep learning methods represented by convolutional neural network (CNN) [24] and recurrent neural network (RNN) [25] have received extensive attention. Since 2018, pre-trained language models represented by bidirectional encoder representations from transformers (BERT) [28] have opened a new era in the field of natural language processing. The application of deep language representation models with the "pre-training-fine-tuning" paradigm as the core has become the mainstream approach.

Application of BERT and its improved models to text classification has become widespread. BERT- CNN is proposed for the classification of candidate causal sentences [24], Chinese sensitive text information [29] and fake news on COVID-19 [30], [31], making significantly better effect than the most advanced baseline model. BERT- BiLSTM is used in medical text inference [16], sentiment analysis based on social media online comments [32] and movie reviews [27]. It can also complete the extraction of local features of Chinese medical texts, helping improve the medical service [26].

BERT-BiGRU is another common combination model for text classification. BERT-BiGRU model has better performance in the Chinese text classification task when compared to word2vec-BiGRU, BERT-CNN and BERT-RNN [33]. This model can have good text classification effects both in questions and answers on legal text [34] and academic papers [35]. It can be shown that using different BERTlogy pre-trained language models to conduct text classification research has become the mainstream research method.

B. PERSONALITY TRAIT RECOGNITION

Personality traits refer to the unique and stable way of thinking and behaving on consistent basis. Many studies have been related to judging personality traits based on linguistic cues in text content. It has been stated that strangers could accurately judge an individual's personality traits by reading the content revealed by the individual's free consciousness [36]. Based on the self-description, sub-clinical depression in an individual can also be identified [37].

Increase in the frequency of computer-based communication and social networking use has opened up new opportunities for researchers to detect personality traits through various channels such as email interactions [38], user name settings in online games [39], and tweets [40]. It is found that users of social networks extend their personalities in the real world through social networks [41]. The text content can be used to recognize emotion and personality traits [42]. In short, information in the network platform published by the individual can reflect the individual's personality traits.

The trait recognition through deep learning methods has been the focus of some previous studies. A text-based personality trait classification deep learning model is proposed to improve classification accuracy and reducing calculation time [43], [44]. For example, a deep learning- based document model was proposed to recognize the personality traits according to the text content from Facebook messages and Tweets [40], [45].

C. NOVELTY SEEKING

Novelty seeking (NS) is one of personality traits that refers to a tendency to pursue new experiences with intense emotional sensation [9] and an influential element of motivational behavior [46]. NS personality is related closely to the revisit intention, loyalty and satisfaction in the tourism industry. Satisfaction plays a mediating role in the influence of novelty seeking and familiarity on revisit intention [10], [11]. The evidence to support some of the propositions that tourists with a tendency to NS shows a variety of destination patterns and therefore tend to return to the same destination [47]. The concept of optimal stimulus level was used to analyze the role of NS in selecting tourist destinations to understand better the loyalty of tourists [48]. NS has a mediating effect between satisfaction with the two motives of outdoor activities and holiday style loyalty [49].

In previous research, NS is measured using scales and data collection is done through questionnaires. NS measurement scales is usually revised and supplemented according to the previous mature scale. A 4- dimensional NS scale including external sensation (ES), internal sensation (IS), external cognition (EC) and internal cognition (IC) [50] was improved into thrill, change from routine, boredom alleviation, and surprise [46]. A three-dimensional personality questionnaire (TPQ) was used to evaluate the NS [51], which found that the NS is a personality trait positively related to increased body mass index (BMI) and obesity. A new cross-domain recommendation scenario based on deep learning was proposed to mine NS features of movie, music and book domains from the social media platform data [52].

Limitations associated with the questionnaire method regarding small sample size, lack of representation of diverse demographic groups and the certain guiding nature of the questions, can affect the recognition NS traits and its possible effects. Moreover, questionnaires for both academic and practitioners are known to be time consuming and resource intensive. Given the availability of vast amount of online data, deep learning methods can be used to identify different personality traits rather accurately. Toward this end, this study synthesizes previous scales and develop a new NS measurement scale useful for classifying NS personality using deep learning on online user comments.

Through the review and analysis of relevant literature, it is found that deep learning, as a cutting-edge machine learning method, has been gradually applied and performance well in the field of NPL and text classification. NS plays an important role in the tourism industry, and its identification remains in the traditional subjective and inefficient methods, and few scholars have conducted systematic research on its identification. Recognizing NS personality traits from text information has proven to be feasible. The comments made by Internet users on major network social platforms and forums can be used as important information for NS personality analysis. Recognition methods gradually develop from inefficient and costly manual recognition to efficient deep learning. Therefore, BERT- BiGRU based on the NS multi-dimension is put forwarded to recognizing NS personality traits, providing a basis for the personalized tourism of tourists and the refined operation and decision making of tourism managers.

III. METHODOLOGY

This section mainly introduces the key steps of NS recognition based on the BERT- BiGRU deep learning model, including developing and validating the model, data collection and preprocessing, construction of NS scale, and creating training data.

A. DEVELOPING AND VALIDATING THE DEEP LEARNING MODEL

The identification and classification of NS-based on scales is one of the research methods recognized by scholars for a long time. Therefore, based on previous studies, a NS scale was extracted and summarized. Then, the crawler software Octopus Collectors was used for data collection. Special characters, emoticons and hyperlinks are removed through preprocessing, and the preprocessed text is calibrated based on the training set based on the NS scale.

The pre-training language model BERT uses a multi-layer two-way Transformer structure as an encoder, and combines the masking language model and the next sentence prediction two unsupervised predictive subtasks to complete the pre-training. Compared with other language models, BERT can make full use of word context information to create high-quality contextual word vectors for various natural language processing tasks [33]. When the RNN model is trained for back propagation, the gradient cannot be passed on for a long time in a longer sequence. So, the gradient will disappear, and the gated recurrent unit (GRU) [27] network can be used to solve the problem of long-term memory. However, the GRU network can only process one-way time series, and the contextual information in the text is highly correlated. One-way processing will miss much information. For this reason, BiGRU is proposed and adopted as a deep learning model. In order to improve the quality of input data.

The specific design of the framework is shown in Figure 1. The model includes four sections: construction of NS scale, data acquisition and preprocessing, creating training set, NS recognition and result evaluation. The working of BERT-BiGRU is divided into three parts: First, the semantic representation of each text is obtained through BERT model training, and the vector representation of words is obtained. Then the vector representation of the word is input into the BiGRU model for semantic analysis and extraction. Finally, the final word vector is connected to the softmax layer for text classification.

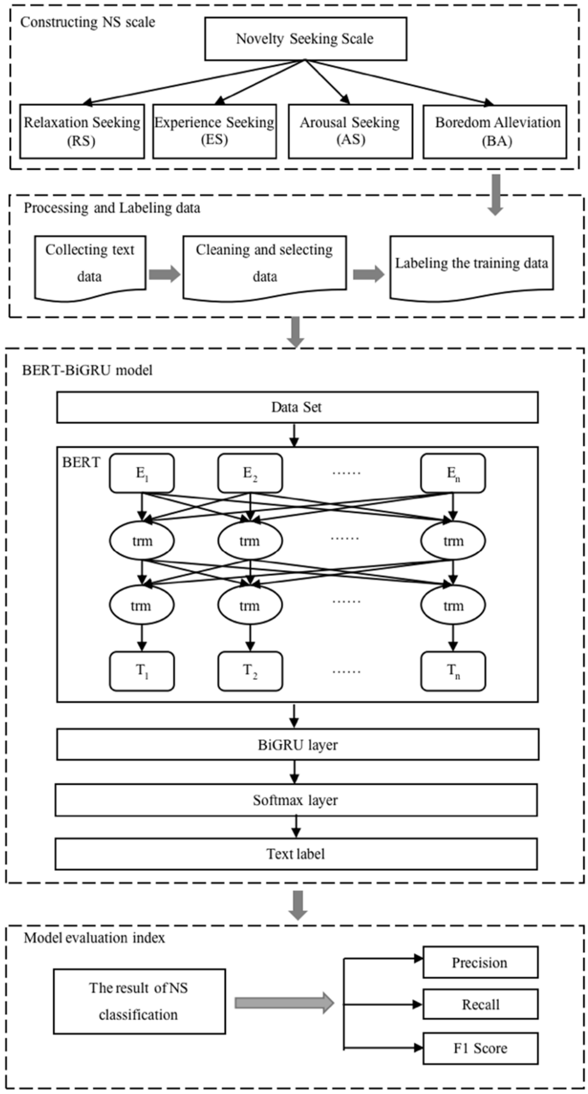

FIGURE 1. Framework of NS recognition model.

B. DATA COLLECTION AND PREPROCESSING

Data in this study is collected from TripAdvisor which is an online travel information website containing a large a of user reviews. The website effectively reviews the reviews, which help in reducing spam, fraudulent information and noise data unrelated to scenic spots on a large scale. For demographic variation and regional distribution, data collection in this study focused on reviews on ten tourist attractions found in the ''Travelers' Choice'' list of 2020. The ten attractions are Colosseum (Italy), Old Quarter (Vietnam), Mutianyu Great Wall (China), South Beach (U.S.A.), Piazza San Marco (Italy), Burj Khalifa (Dubai), Sea Fortress (Finland), Hagia Sophia (Turkey), La Petite (France), Lake Lucerne (Germany). The Octopus Collector, a web crawler software, was used to take the first 3000 user reviews of each scenic spot, a total of 30 000 pieces of data were collected. In order to reduce the noise of experimental data, we deleted advertisements and duplicate reviews, resulting in a final experimental dataset of 28959 reviews.

After collecting the data required by the experiment, the data is usually required to be preprocessed. Due to good review mechanism of the TripAdvisor, the probability of noise data and advertisements was greatly reduced. In the process of preprocessing English text, stop words refer to filtering out some frequently used but meaningless words. The purpose is to reduce the dimension of feature selection attributes, so as to reduce the amount of system calculations and improve the efficiency of analysis results. Stop words mainly include articles, prepositions, numerals, interjections, etc. For example, common English stop words include ''a \ an'', ''the'', ''of \ off'' and so on. Sometimes, in practical applications, some real words that have practical meaning but have little effect on the analysis results can be removed. Lowercase need to be converted to uppercase.

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TABLE 1. Multidimensional scale of NS.

Dimension	Corresponding items from multi-dimensional novelty-seeking scales	Lee& Crompton (1992)	Jang& Feng (2007)	Kitouna & Kim (2017)	Nguyen et al. (2020)
Relaxation seeking (RS) /Relaxation (RL)	Find myself in nature where I explore new things	✓		✓	✓
	Relax and experience peace among the natural environment			✓	✓
	Go back to nature because my life is associated with urban life			✓	✓
	Enjoy the natural atmosphere				✓
	Relax after stressful working days				✓
	Enjoy and view the scenic beauty of nature			✓	
Experience seeking (ES) /Novelty learning (NL) / Change from Routine (CFR)	Experience different cultures and custom (local festivals and rituals)	✓	✓	✓	✓
	Widen my knowledge about people and the nature of these destinations		✓	✓	✓
	Explore new destinations	✓			✓
	Meet new and interesting people		✓	✓	
	Try a new taste of local cuisine and food		✓	✓	✓
	Try local crafts and handiwork		✓		
	Experience the new and different things that I have not seen before	✓		✓	
	Experience unique aboriginal or native group		✓	✓	
	Variety of things to see and do		✓		
	Visiting a place I can talk about when I get home		✓		
	See or experience people from different ethnic backgrounds		✓		
Arousal seeking (AS)/ Adventure (AT)/ Thrill(TR)/ Surprise（SP）	Take off on a trip with no preplanned or definite routes, or time table	✓			✓
	Seek adventure on my vacation	✓		✓	✓
	See the mysterious sceneries				✓
	Explore the unknown on vacation	✓		✓	✓
	Be a sense of discovery involved	✓			
	Enjoy the change of environment, which allows me to experience something new on vacation				✓
	Enjoy doing activities that offer thrills	✓		✓	
	Enjoy experiencing a sense of danger on a trip	✓		✓	
	Experience the excitement on my vacation			✓	
	Enjoy doing frightening or daring things on vacation	✓			
	It is fun to be a little scared on vacation	✓			
	Be on a raft in the middle of a wild river at the time of the spring flood waters	✓			
Boredom alleviation (BA)/ Boredom relief (BR)	Like to go to the nature destination for my vacation in order to get rid of the rut	✓			
	Like unexpected people/friends				✓
	Go traveling because I don't want to repeat my daily routine				✓
	Like vacations that are unpredictable	✓			
	Like to travel because the same routine Work bores me	✓			✓
	Travel to relieve boredom	✓			✓

C. CONSTRUCTION OF NOVELTY SEEKING SCALE

One-dimensional scale does not capture different attributes of the complex personality related phenomenon of NS. In previous research many studies have used multidimensional scales for measuring NS [15], [46], [53]. These scales and their dimensions have been provided in table 1. In this study a four-dimensional scale based on previous studies was used. It includes relaxation seeking, experience seeking, arousal seeking and boredom alleviation [15].

As can be seen from the table 1, there is a clear link between different dimensions measured in different scales in a way that though names are different they capture more or less the same attributes of NS. Therefore, we merged dimensions with overlapping concepts. Even semantics of multiple items in the four dimensions are similar or consistent, so they are merged into the same dimension to streamline the same items. After merging different dimensions, we ended up with a four-dimensional scale of NS consisting of relaxation seeking (RS) (including RS and RL), experience seeking (ES) (including ES, NL and CFR), arousal seeking (AS) (including AS, AT, TR and SP) and boredom alleviation (BA) (including BA and BR).

Relaxation seeking motives of human behavior is defined as escaping from everyday life and relaxing, which have significant impact on travel decisions. Relaxation is a term often used in travel industry surveys, but the definition of this term is contradictory for visitors. Some visitors say they feel comfortable and relaxed in the destination, but they also admit of being tired after returning home.

Experience seeking refers to the expectations regarding unprecedented new experiences, such as enjoying life and making new friends in different ways. Experience is an important part of NS. When tourists arrive at their destination, they do not need to worry about being published or losing rewards for learning during these journeys. The local culture, history and lifestyle of different tourist locations provide tourists with various experiences.

Excitement seeking refers to a sense of excitement gained through involvement in strange, dangerous, unusual, or unknown situations. Many people try to seek adventure during the journey. Studies have shown that people with low NS feel comfortable in a familiar working environment. When scheduling vacations, they will carefully plan their journeys to avoid accidents. After selecting a destination, they usually choose the same location every year in all the journeys. People with high NS would rather go to unique places and may change their itinerary during the journey.

Relieving boredom is an act that reduces or eliminates the thoughts that visitors have when they are at home. Boredom is a human emotional state, especially when work arrangements and repetitive behaviors restrict life. When people realize that they live in an environment with many fixed and predictable things, they are more likely to be bored than when they are in a changeable environment. The feelings of boredom and discomfort are usually associated with compulsion and repetition. It is a basic human need to alleviate boredom through seeking new activities.

D. CREATING THE TRAINING DATA

After developing the multidimensional NS scale, NS content needs to be labelled in online travel reviews to obtain the training set to train the NS recognition model based on deep learning. Three people including one researcher, one undergraduate student and one teacher majoring in the information science, independently and manually coded the data. Neither of them was familiar with the research methodology or the NS field. The student had a work experience in a travel agency. He has some insights into understanding the emotions expressed in tourists' comments.

The three people including one principle investigator and two research assistants independently manually coded the data. Both research assistants are graduate students majoring in information management. The principal researcher is familiar with the research, methods, and NS, but the associate researcher is not familiar with these areas. Therefore, assistants can be considered objective in terms of research. The research assistants were given a spreadsheet with classification rules, including each dimension's details and example reviews. As for classification, the researcher uses a multidimensional scale to judge whether text reviews are NS. For example, the comment " *If you have only 1 day in Rome, then do nothing except visiting the Colosseum (of course in addition to tasting Gelato and the delicious Italian cuisine).* " expressing the willingness of tourists to try local food, is classified as "experience seeking". "*Very nice small area with old buildings and restaurants and more. Great breathtaking views and relaxing feel.*" expresses the relaxed and calm mood of tourists, and is classified as "relaxation seeking". As long as a text comment meets a certain NS evaluation criterion in any dimension, the comment is marked as "1", which means that it has NS tendency. Conversely, if no sentence meets the dimensions of the NS scale, the comment is marked as "0", that is, it does not have NS.

To facilitate manual labeling, a list of indicative words can be created. The explicit inclusion of these directives in online travel reviews can be considered obtaining NS, but it should not be limited. For example, some comments do not contain the words "enjoy nature", but the comment "*the whole park is full of flowers and plants, full of greenery, beautiful scenery, and is a natural oxygen bar*" can also reflect the pleasure of tourists enjoying the natural atmosphere at this time. So, this comment should also be marked as "1".

According to the four dimensions of the NS scale, a list of indicative words for each dimension was created to facilitate the coding and add words and synonyms that can directly express each measure to the list of NS indicative words. For example, the most important keywords in the RS dimension are "relax", "calm", etc., and related words that may appear in the comments are "soften", "calm down", "take it easy", and "take a break". In the ES dimension, indicative words that can be used as "interesting things" need to express the characteristic of being interesting through words such as "amusing", "attractive", and "curious". According to this regulation, a list of pointers is shown in Table 2.

The markers should label the reviews according to individuals' understanding or the indicative words. The labeled content is used as the training set. Examples of the annotated data are shown in Table 3.

After the principal researcher completed classifying the online travel reviews, two assistant researchers were provided with a document with indicative words and rules. Their task was to mark the comments as "1" when containing NS tendency or "0" if not, and put the comments which class they thought it belonged to. When there is a disagreement during marking and checking data, the labelling result should depend on at least two identical judgments. Fleiss' Kappa coefficient is applicable to retest consistency or observer consistency test when repeated measurements are analyzed for 3 or more times and the results are disordered categorical variables [54].

TABLE 2. List of indicative words.

Dimension	NS scales	Indicative words
Relaxing Seeking (RS)	Enjoy the atmosphere of nature Tranquility in the natural environment Return to nature Explore nature Natural wonders Relax, calm	View, spot, landscape, scenery, soften, calm down, take it easy, ease off, feel at home, loosen up, take a break, cool off
Experience Seeking (ES)	Explore new destinations Taste local delicacies Know the local people (indigenous) Seek experience Interesting things Experience different cultures and custom Local festivals and ceremonies	Fresh, unfamiliar, novel, daintiness, delicious, tasty, native, original, aboriginal, autochthonous, experience, assuming, attractive, curious, intriguing, striking, cultures, art, classical, festival, commemoration, holiday, ceremony, rituals
Arousal Seeking (AS)	Seek adventure Unplanned journey Mysterious scenery Explore the unknown desire Experience something new Things that bring excitement Like danger Scary/bold things	Adventure, accidental, unintentional, purposeless, unplanned, covert, secret, mysterious, mystery, unidentified, undiscovered, mysterious, thrill, hazard, risk, uncertainty, treat, scared, daring, bold, adventurous, fearless
Boredom alleviation (BA)	Relieve boredom Unexpected person/friend Bored with the immutable things Don't want to repeat daily life Get rid of the monotony Experience things you haven't seen	relieve monotony, surprising, amazing, unforeseen, unpredictable, mutable, get rid of monotony

The SPSS 26.0 was used to calculate the degree of agreement, showing the accuracy of the test classification as 0.72, suggesting substantial agreement.

The accuracy of classification was also verified by randomly dividing all available labeled data into training set, validation set and test set at a ratio of 8:1:1. The training set is used to train the model, and the validation set is used to evaluate the prediction of the model and adjust the corresponding parameters, which need to be labeled [55]. A random list of 28959 online reviews were manually labelled. Table 4 displays the training data after these efforts, which shows that 55.54% of the comments depicted NS sentiment and 44.46% did not. The data are available on the GitHub software repository (https://github.com/rwqzcq/Novelty-seeking-Classification-and-Error-Analysis.git).

IV. FINDINGS

This section is mainly based on the NS recognition model and the travel online reviews collected by last section to carry out empirical results. The findings are analyzed from three perspectives including experimental evaluation index, comparison experiments and error analysis.

A. EXPERIMENTAL EVALUATION INDEX

To investigate the model performance in detail, the authors computed a confusion matrix that shows the accuracy of recognition [56]. Based on the confusion matrix, we can calculate the precision, recall and F1 score of the deep learning model. The F1 score as the harmonic average of the accuracy and the recall rate can better balance the performance of the two [57]. Therefore, F1 score are the main indicator for experimental evaluation, recall and precision values are

TABLE 3. User reviews NS labelling examples.

Review	NS	Involving dimensions
Beautiful historic gem located by the blue mosque. The architecture is marvelous and the place has a **serenely peaceful feeling**. At the moment be ready to queue up if you want to go in and you will need to go through security checks also. I waited over an hour to get in but it was well worth it.	1	Taste local culture/ Relax, calm
We walked along the fortifications, crossing from one island to the other and **enjoying the beautiful views of the coast and sea surrounded by blooming flowers**	1	Enjoy the atmosphere of nature
Visited here for the second time last spring and first time getting a proper full day. You can get a return ferry ticket nowadays for just €5 and **the Island was beautiful and surprisingly quiet** when we went. It's a combination of nature and history and really, it's just a nice place to go for a walk.	1	Enjoy the atmosphere of nature/quiet
If you are looking to **relax and have a quiet day** this is not the place. It is a busy area and people are hustling. **Everyone is extremely friendly** and they have a lot of street food their to try.	1	Relax, calm/ local people
Great area for shopping (do haggle), stuffed freshly baked buns, fresh ales & brews, **local foods & local culture.**	1	Taste local delicacies/culture
Our tour guide Angela was delightful and our driver seemed to have a ready stock of secret shortcuts. It being the **Autumn Festival** weekend, there were hordes of day trippers from Beijing.	1	Experience different cultures and custom
Very little to see as the place is going through renovations. They make you cover your legs and head. They provide if you don't have it.	0	
It's a one of those places you won't forget you visited because of its rich work. The paintings on the walls are so beautiful and spiritual.	0	
This is really one of the nice place in istanbul in the best area in front of sultan ahmat recommend to see it	0	
Loved it, visited at midnight was one of the only people in the place. No fee to enter now as it is now a mosque.	0	
So expecting a museum we entered a mosque instead and it was Friday and man i do not recommend going there in friday. The most crowded day for people who come to pray. We really couldnt see much as a respect we left...	0	
Definitely a place to see day and night time. Great architecture inside the building. Most busy place for pictures from 12 till 6 pm. Best time is always till 10 am.	0	

auxiliary reference indicators. The calculation formulas are as follows [57]:

$$Precision = \frac{TP}{TP + FP} \tag{1}$$

$$Recall = \frac{TP}{TP + FN} \tag{2}$$

$$F1 = \frac{2 \times Precision \times Recall}{Precision + Recall} \tag{3}$$

B. COMPARISON EXPERIMENT

Since the structure of the model belongs to supervised machine learning content, it is necessary to design a certain amount of training set data to train the text's NS in deep learning by means of manual annotation. After acquiring and pre-processing the data [58], manual labeling of NS is carried out according to the multidimensional NS scale. Then train the BERT-BiGRU model which is constructed according to the Figure 1. The experimental environment and configuration are shown in Table 5, and the training parameters are shown in Table 6.

TABLE 4. Descriptive statistics of training data.

Dimension	Number	Proportion
Relaxing Seeking	4483	15.48%
Experience Seeking	4596	15.87%
Arousal Seeking	711	2.46%
Boredom Alleviation	3085	10.65%
Non-NS	16084	55.54%
Total	28959	100%

In order to verify the effectiveness of the model constructed in this article, the authors try to use the method of controlling

TABLE 5. Experimental environment and configuration.

Environment and configuration	Value
Operating system	Linux
Processor	Xeon Gold 6142
RAM	60.9G
Programming language	Python3.7
Deep learning framework	Pytorch

TABLE 6. Model parameters.

Model parameters	Value
bert model	Bert-base-uncased
optimizer	adam
loss function	cross-entropy loss
batch_size	8
learning_rate	0.0001
dropout_rate	0.5
epoch	20
layers	2

variables and keep one of BERT or BiGRU to prove that the collocation effect of these two models is the best. The other Word2vec, CNN and RNN that are replaced are all mainstream classical deep learning models. This section designs a model comparison experiment to compare the BERT-BiGRU model in this article with the three models of Word2vec-BiGRU, Glove-BiGRU, ELMo-BiGRU, BERT-LSTM, and Word2Vec-CNN.

(1) Word2vec is the basis to develop BERT, so the labeled text information is preprocessed through the Word2vec model, followed by BiGRU, only change the language preprocessing model, and then the BiGRU model is used to identify the NS of the output results. Word2vec-BiGRU was used to classify the bacterial virulence factors and achieve good performance with accuracy and F1 score [59].

(2) Global Vectors for Word Representation (Glove) The Glove algorithm is a regression algorithm based on global word frequency statistics.Glove- BiGRU has achieved good performance in the research of large-scale academic paper topic classification based on deep attention neural network [60].

(3) Embedding from Language Models (ELMo) is used to solve the polysemy of words. The input text is represented by the word vectors obtained after the training of ELMo model, and these word vectors are used as the word embedding layer to access the BiGRU model for feature extraction and classification.

(4) The annotated text information is preprocessed through the BERT model, without changing the language preprocessing model, followed by LSTM, only changing the deep learning model, and then using the traditional LSTM model to identify the output results for NS. BERT-LSTM was widely used in the field of sentiment analysis based on the online comments [32].

(5) This model changes both the preprocessing model and the deep learning model, select the model that is often used in previous research, convert the labeled text information into the corresponding word vector through BERT, and then use the CNN model to classify the word vector. BERT-CNN has been used in classifying news articles and tweets by collecting online news and Twitter, indicating significant improvement in the accuracy of other classification model [61].

The experimental results are obtained through the above experimental content, indicating that the research on recognizing NS based on the BERT-BiGRU model can achieve precision and F1 of 93.4% and 93.3% separately in TripAdvisor users' comments on scenic spots. More than 80% of the current emotion classification research is based on machine learning.

The results of the comparative experiment are shown in Table 7 and Figure 2.

TABLE 7. Test results of different models.

Model	Precision	Recall	F1
BERT- BiGRU	**93.4%**	**93.2%**	**93.3%**
Word2vec-BiGRU [33]	91.2%	75.1%	82.3%
Glove-BiGRU [60]	90.2%	91.0%	89.7%
ELMo-BiGRU [33]	86.9%	85.6%	86.4%
BERT-CNN [62]	83.4%	79.3%	81.4%
BERT- LSTM [63]	83.6%	81.2%	82.5%

According to the results shown in the figure, the model selected in this research has obvious advantages compared with other comparative text classification models. The precision, recall and F1 score of the BERT-BiGRU model are higher than those of other comparison models. The effectiveness of BERT is verified by comparison of these models. The word vector representation method of word2vec and Glove could not solve the polysemy problem in different environments. ELMo model is adopted to solve the polysemy problem of words. The experimental results show that the performance of ELMo model is improved compared with word2vec and Glove, but the evaluation index is still worse than BERT. By comparing with BERT-LSTM model and BERT-CNN model, the effectiveness of feature extraction and text classification based on BiGRU model is proved. Although they are both based on BERT model, BiGRU model obtains better semantic features in both forward and

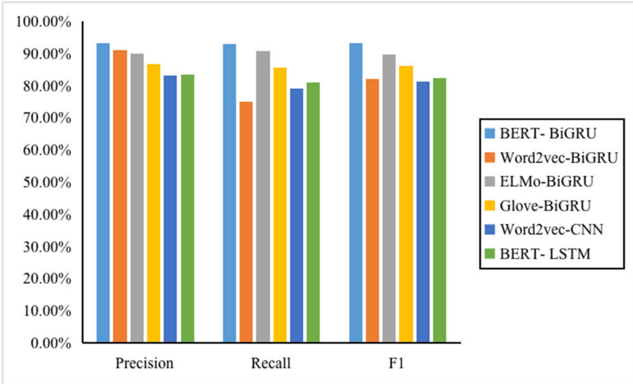

FIGURE 2. Comparison results of each model.

backward aspects than CNN and LSTM neural networks. Overall, the BERT-BiGRU-based travel online reviews NS recognition model can identify the NS tendency of user reviews of tourist attractions more effective than these comparative experimental models. The model meets the expected requirements and has achieved good results.

C. ERROR ANALYSIS

After the classification results are obtained, error analysis of these results is needed to analyze the specific situation of misclassification more intuitively and to further analyze the causes of misclassification. In the machine learning community, there is a specific matrix that presents a visualization of the performance of an algorithm, called the confusion matrix, which is commonly used for supervised learning algorithms [64]. The columns of the confusion matrix represent the categories predicted by the algorithm, and the rows represent the actual categories. It can clearly show whether the classification results of various categories are confused. Normally this confusion matrix would be shown as a picture.

The confusion matrix is shown in figure 3. This confusion matrix only distinguishes between 0 and 1. Its rows represent the true category and its columns represents the predicted category. Taking the first row as an example, the true category

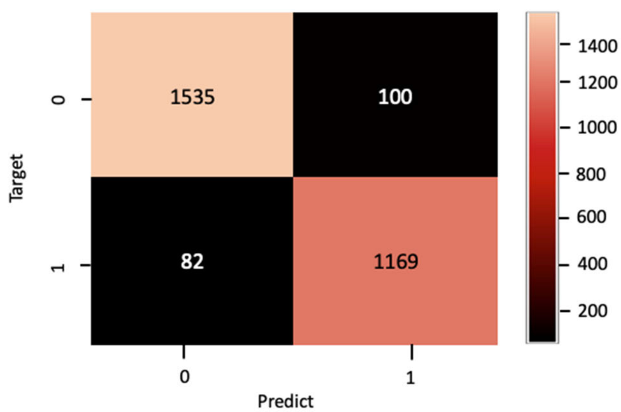

FIGURE 3. Confusion matrix.

label is 0. From the predicted labels in the column direction, 1535 instances are predicted to be 0 and 100 instances are predicted to be 1. That is, of the 1535 instances with true label 0, 1535 were correctly classified and 100 were incorrectly classified. Looking at the second row in the same way, of the 1169 instances in the second row where the true label is 1, 1 prediction are wrong and 1169 predictions are right. This indicates that the model performs good in the "0" and "1" roles, without the overfitting and underfitting.

V. DISCUSSION

In this research, the authors demonstrated an approach for automatically classifying several thousands of online travel reviews with a nuanced classification capturing various dimensions of novelty seeking. NS is a vital motivation for tourism, which plays an inseparable role in the choice of destination and is one of the biggest factors affecting tourists' perception. NS has a significant impact on tourists' return intention, loyalty and satisfaction to the destination. Therefore, the identification of NS from tourists' feedback is of foremost importance for the development of tourism.

From the theoretical point of view, we summarized and improved the NS scales based on the previous work, and enriched the traditional personality measurement tools in psychology. At the same time, the model combining deep learning and measuring scales is applied to the identification of NS, which combines psychology and computer science well, enriching the further research in this field.

It is challenging to develop the training data by using the theoretically derived dimensions, especially during different coders. Theoretically complex NS classification scheme seems to present challenges to obtain consensus among human coders, but substantial consistency (Fleiss' Kappa=0.72) can be obtained as long as effective classification rules can be implemented. It is a good solution to replace abstract expressions in comments with indicative words. Among the dimensions, NS, RS, RS and BA were reviewed with similar frequency (15.48%, 15.87% and 10.65% respectively), while AS had the least proportion (only 2.46%). It seems reasonable that most people will take safety into an important position instead of changeling potentially dangerous activities.

The overall recognition effect of the NS personality trait recognition model based on BERT-BiGRU is satisfactory. In addition to using this deep learning model for NS recognition, it can also be applied to other personality trait recognition when it is necessary to study specific important personality traits or special emotions in a certain field. It is only necessary that the personality traits or emotions have a scale that conforms to scientific rules, and it can be generated by users based on deep learning methods. The text content effectively recognizes these personalities and emotions.

For example, specific scales can measure customers' trust in the company, students' moral feelings, consumers' nostalgia, and employees' tendency to quit. Combined with emotion or personality scale, the corresponding emotion and personality characteristics can be identified through text information such as user's comments on the company website, students' comments on a moral event, consumers' comments on a product, and employees' comments on the company forum.

The personality trait recognition in current research relies heavily on traditional personality traits measurement methods, such as interviews and questionnaires. The disadvantage of using the interview method is that it requires professionals to conduct the assessment and has a large workload and low efficiency. It is not suitable for scenarios with too many research objects. Although the efficiency of questionnaire method is higher than that of the interviews, questionnaires are prone to bias particularly in the absence of interactive guidance from researchers.

Traditional personality trait measurement methods are subjective and static. Application of the deep learning method, as shown in this study to identify personality traits through text information, can be combined with other methods such as interviews to overcome inefficiency and deviations caused by participants' factors. In addition to online comments, deep learning model can also be applied on the interview data for subjects' NS classification which can reduce interviewer bias. The method of personality trait recognition based on deep learning can quickly and efficiently batch process and analysis of imported data information.

Combining deep learning with other NS personality evaluation methods such as questionnaires and interviews can solve both the problem of participant subjectivity and research inefficiency.

VI. CONCLUSION

This research demonstrates the applicability of deep learning in automatically processing substantial amounts of travel online reviews using a theory-based classification of NS personality traits. It proves that personality traits can be effectively and automatically identified based on the advanced computational techniques. However, there are some limitations to this research. NS dimensions are subjective, and the concept involves many dimensions with a high degree of abstraction. In addition to using a simple two-category for novelty recognition, multi-category recognition can also be performed based on the number of dimensions of the scale. Optimization of tourist destination recommendation system based on NS personality can be a further research direction, such as grouping users with NS, improving user portrait understanding and precision marketing.

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