Determinants of Inquiry Responses in Nonprofit Mental Health Forums: An Interpretable Machine Learning Approach

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Abstract

Background: In recent years, there has been a noticeable increase in individuals seeking psychological assistance and therapeutic interventions through virtual mental health platforms. The increasing demands and contributions of users constitute pivotal elements underpinning the development of these online psychological communities. Nevertheless, limited attention has been given to the quality and quantity of information exchange within these virtual mental health forums.

Objective: The primary objective of this study is to investigate the determinants influencing user inquiries and response volumes to queries within virtual mental health forums. This study aims to provide empirical data and theoretical underpinnings, as well as suggestions, to improve the service of online mental health communities.

Methods: This study employs a pretrained deep learning-based natural language processing model named BERT to conduct a thematic analysis of the content in the inquiry and response sections of online mental health communities. In addition, sentiment analysis is performed based on a sentiment dictionary. We then utilize a machine learning method (LightGBM) for predictive analysis of the response volumes. Furthermore, the SHAP analytical technique is employed to better explain the determinants of response behavior.

Results: The findings indicate that user inquiries can be categorized into seven themes: job, love, depressive moods, relationships, school, marriage, and family. The sentiment analysis reveals that topics related to 'relationships' and 'marriage' are associated with positive emotions and high view counts and contribute positively to the number of replies. Conversely, topics such as 'romance' and 'depression' usually carry neutral or adverse emotional tones and negatively impact response rates. Notably, posts with sufficiently high levels of positive or negative emotions tend to receive a higher number of responses.

Conclusions: This study has both theoretical and practical implications for advancing the contribution of user knowledge in online mental health communities, as well as for improving the quality of services provided by these communities.

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Original Manuscript

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Keywords: Online mental health community; response volume; influencing factors
theme analysis; sentiment analysis; predictive analysis

Introduction

Background

Mental health disorders are a critical global health concern, contributing significantly to the overall burden of disease[1-4]. A meta-analysis indicated that individuals with mental health disorders experience a high burden of illness and an increased risk of mortality[5]. Approximately 12% of the global population is estimated to experience mental health disorders, accounting for approximately 5% of disability-adjusted life years [6]. A recent World Health Organization report on global mental health indicates that approximately one billion individuals worldwide (representing more than 12.5% of adults and adolescents) are affected by mental health conditions. Data from the China Mental Health Survey (CMHS) revealed that the adjusted lifetime occurrence of mental health issues in China, excluding dementia, is approximately 16.6%. Therefore, raising awareness of mental health, strengthening mental health services, and promoting a holistic approach to both the physical and mental health of individuals have emerged as significant research issues[19].

With the advent of web-based services, online psychological counseling has gained increasing attention and participation. In China, an increasing number of mental health forums have recently been established, e.g., Yi Psychology, Simple Psychology, Yi Dian Ling, and Songguo Qingshu. These platforms connect patients and doctors online, transforming the traditional doctor–patient communication model[20]. There are two main groups of users in these online mental health communities: users who seek psychological support and psychological counselors who offer psychological support[7]. Studies indicate that many people tend to conceal their mental health problems due to the stigma associated with mental illness[8], making online mental health communities a more accessible option[21]. In addition to offering informational and emotional support through cost-free inquiry, posting and responding, some online mental health communities also provide online consultation services and posttreatment monitoring with payments. These platform settings enable users to express feelings, exchange opinions, gain recognition, and assist others[22].

Current studies on online mental health can be classified into three main categories: studies that focus on users[9-11], studies that focus on information[12, 13], and studies that focus on communities[14]. User participation plays a crucial role in the sustainable development of online mental health communities. However, most studies focus on the demand side[10, 15-16]. The contribution of information providers in these communities also significantly impacts the quality of information and consultation services. Therefore, it is necessary to focus on mental health information providers, explore the factors that influence knowledge contributions in online mental health communities, enhance user satisfaction and foster the development of online mental health communities[23].

In online health communities, the contribution of knowledge has emerged as a critical factor driving community development and has increased the attention given to the motivations and influencing factors that support or hinder users' knowledge-sharing behaviors[17, 18]. Knowledge contribution involves the process by which individuals actively contribute, share, and engage in the generation of knowledge within virtual communities. The factors influencing knowledge contribution behaviors vary across different user groups and types of contributions[24]. These factors can generally be divided into question-related factors, such as question content; community-related factors, such as reward mechanisms; and answer provider-related factors, such as social relationships, self-efficacy, and reputation needs [12]. In addition, the characteristics of posts, such as view counts and posting times, may impact the knowledge contributions of professionals. Therefore, it is necessary to explore the role of post characteristics in influencing professionals' knowledge contributions.

Furthermore, when analyzing the motivations behind knowledge contributions by users in online health communities, existing studies often employ traditional statistical analysis methods such as structural equation modeling and multiple linear regression. These methods explore how variations in different factors affect the willingness or behavior of online health community (OHC) users to contribute knowledge. However, traditional regression methods have several limitations. For example, linear regression models assume a direct correlation between input and output variables and are susceptible to anomalies. With the rapid advancement of artificial intelligence (AI) technology and the continuous evolution of machine learning algorithms, more robust methods have been introduced for modeling, delineating, and interpreting complex interrelations among diverse factors. Compare to random forests and logistic regression, the light gradient boosting machine (LightGBM) is a faster, distributed, and efficient gradient boosting system based on tree-based algorithms. This framework effectively mitigates overfitting, minimizes the time required to determine the optimal tree depth, lowers error rates, and enhances the precision of predictions.

Therefore, the present study focuses on the content of the public welfare answer column in the Yi Dian Ling online mental health community. The bidirectional encoder representations from transformers (BERT) topic model for thematic and thematic evolution analysis of Q&A content. Additionally, sentiment analysis is conducted on the posts, and emotional features are extracted. By considering thematic and emotional features, along with other characteristics of the posts as independent variables and response volume as the dependent variable, predictive analysis is performed on the response volume. The SHapley Additive exPlanations (SHAP) method is used to interpret the impact of each feature on the response volume, providing suggestions on the basis of the analysis results.

Methods

The research framework for this study is shown in Figure 1. This framework consists of four main steps: data collection, thematic and sentiment analysis, predictive model construction, and predictive model interpretation.

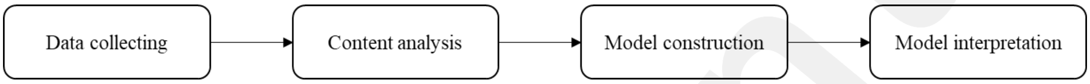

Figure 1 Data analysis road map

Data collection

Data from Yi Dian Ling public welfare Q&A section were collected using the Octopus crawler, comprising 137,243 entries spanning from July 2019 to June 2021. The characteristics of the data are depicted in Figure 2.

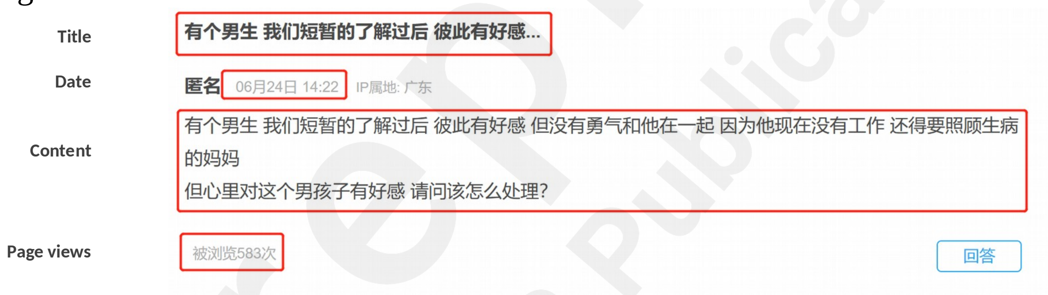

Figure 1 Example of extracted features for the post

Content analysis

Topic analysis

BERTopic has demonstrated advantages in various benchmark tests for topic modeling clustering methods. In contrast to latent dirichlet allocation, the correlated topic model , and other similar models, BERTopic effectively addresses interoperability challenges between density-focused clustering and centroid-oriented methodologies. Therefore, this study employs the BERT model for thematic analysis. BERTopic is a topic modeling technique based on BERT word vectors. This approach facilitates consistent topic identification by leveraging a category-specific version of the term frequency-inverse document frequency (TF-IDF). In this technique, all texts in a cluster are considered one entity, and TF-IDF is applied to determine the relevance scores of words within that cluster. By extracting important words in each cluster, descriptions of topics are obtained. This method is known as class-based TF-IDF (c-TF-IDF):

$$W_{x,c}=¿\vee t,f_{x,c}\vee¿\times\log\left(1+\frac{A}{f_x}\right) \qquad (1)$$

In this context, $t,f_{x,c}$ represents the frequency of word x in cluster c, f_x denotes the frequency of word x across all clusters, and A signifies the average number of words contained in each cluster.

Sentiment analysis

In this study, posttopic clustering and noise reduction are central to the analysis. Sentiment categorization is performed using a sentiment lexicon, which assigns each query a sentiment score. Given the influence of lexicon quality on sentiment categorization accuracy, the semantic orientation pointwise mutual information (SO-PMI) technique is used to effectively create a specialized sentiment lexicon tailored to the content of the psychological service platform. The core concept of SO-PMI involves two arrays of emotion-related words: one positive and one negative. The PMI between each word and those in two sentiment lists is calculated, where P_w represents the list of positive sentiment words and Q_w represents the list of negative sentiment words.

$$SO-PMI(word)=\sum_{P_{word}\in P_w} PMI(word, P_{word}) - \sum_{Q_{word}\in Q_w} PMI(word, Q_{word}) \quad (2)$$

The CNKI sentiment dictionary serve as as the base sentiment dictionary for this analysis. The SO-PMI algorithm is applied to build a domain-specific dictionary. From the output of the candidate words, those with clear emotional tendencies are selected and added to the dictionary. The base sentiment dictionary is integrated with the dictionary constructed through the SO-PMI algorithm to form a complete dictionary. To determine the emotional tendency of each post, sentence segmentation and word segmentation are performed. If a word belongs to the positive sentiment dictionary, the count of positive words is increased by one; if it belongs to the negative sentiment dictionary, the count of negative words is increased by one. Additionally, it is necessary to determine whether there are degree adverbs before positive or negative sentiment words. Various dictionaries are used to account for superlative, comparative level 1, comparative level 2, minor degree, relative degree, and negation words. Weights are assigned as follows: 2, 1.75, 1.5, 1.25, 0.25, and -1, respectively. These weights are then multiplied by the corresponding sentiment word scores. Finally, the emotional value of a post is calculated as the difference between positive and negative emotional values, which determines the emotional tendency of the post.

Model construction

Compared with random forests and logistic regression, the LightGBM provides a fast, scalable, and efficient gradient boosting architecture on the basis of decision tree methodologies. A histogram algorithm is used to split data, allowing for traversing discretized statistics to identify the optimal splitting point, thereby reducing memory usage and increasing training speed. The LightGBM effectively mitigates overfitting, shortens the time to find the optimal depth of trees, reduces errors, and improves prediction accuracy. Therefore, this study uses the LightGBM model for regression prediction. Each question’s content is categorized through topic clustering and sentiment classification to obtain corresponding thematic and sentiment category labels. The selected variables include the question's topic, sentiment category, sentiment score, title length, content length, posting year, posting month, posting date, public holiday status, time of day, day of week, and view count, with the number of responses serving as the dependent variable. After removing duplicate and outlier values, the LightGBM model is used with a dataset splint into 70% training data and 30% test data. The data are randomly divided five times, and the average of the five model results is considered for model evaluation.

Model interpretation

The SHAP approach is an additive model for explanations, developed on the basis of cooperative game theory principles. This approach evaluates each feature's influence on the forecasted outcome using the Shapley value, a concept derived from cooperative game theory. Studies have shown that the SHAP explanation method provides strong interpretability on the basis of machine learning models, making it an effective explanatory tool. In this study, SHAP values are applied for model interpretation. Each predictive sample is assigned a calculated prediction value. The SHAP value represents the quantified contribution of each feature in that specific sample. The explanation is as follows.

Consider the i^{th} sample as x_i, where x_{ij} represents the j^{th} feature of the i^{th} sample, and y_i denotes the model's forecast for this sample. The baseline forecast for the model (often the average of the target variable across all samples) is denoted as y_{base}. The SHAP value is then derived based on the following formula:

$$y_i = y_{base} + f(x_{i1}) + f(x_{i2}) + \ldots + f(x_{ik}) \quad (3)$$

where $f(x_{ij})$ denotes the SHAP value for x_{ij}, indicating the influence of the j^{th} feature of the i^{th} sample on the ultimate prediction y_i. A positive value suggests that the feature enhances the prediction, whereas a negative $f(x_{ij})$ indicates a diminishing effect on the predicted outcome. SHAP values effectively highlight the influence of each feature across samples, delineating whether their effect is constructive or detrimental.

Results

Topic analysis and sentiment analysis

From July 2019 to June 2021, thematic modeling visualization revealed a total of 8 themes, as shown in Figure 3. Clusters assigned a category index of -1 are considered noise and should be excluded. These clusters are represented as gray areas in the figure. Representative keywords for each theme are provided in the appendix.

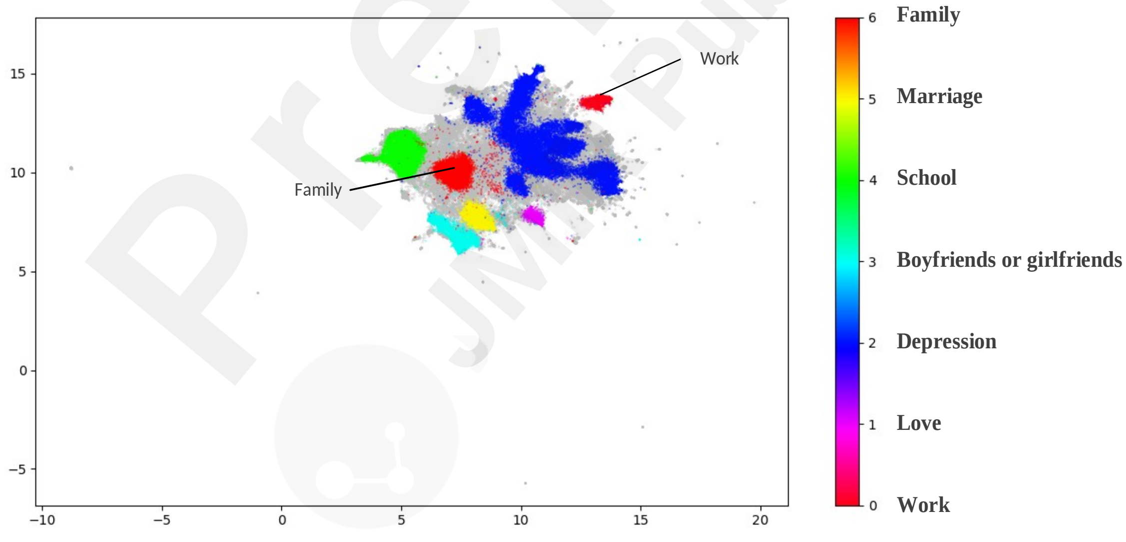

Figure 3 Topic clustering results

Additionally, on the basis of the results of thematic clustering, we calculated the frequency of different themes over various periods, as shown in Figure 4.

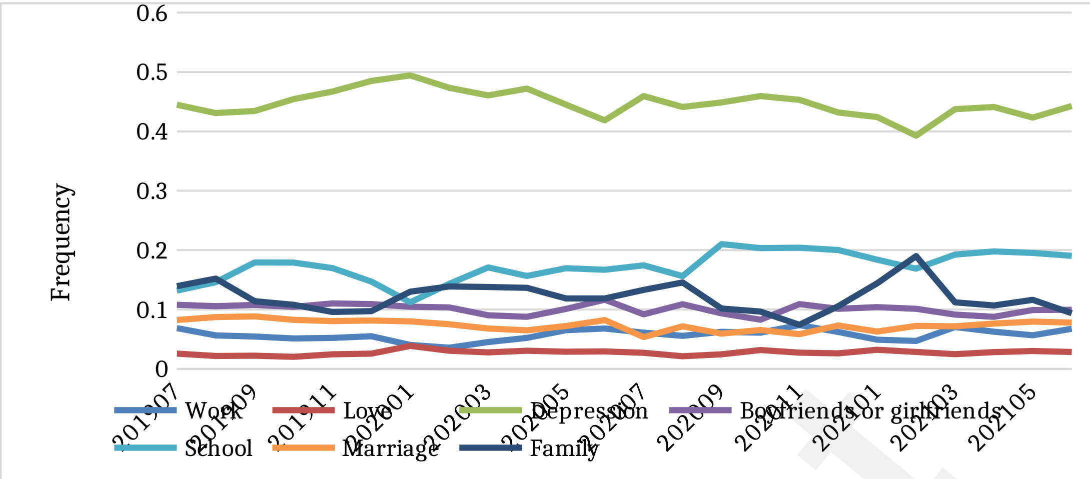

Figure 4 Topic frequency evolution

We used samples after thematic clustering and noise point removal, comprising a total of 64,237 data entries. The SO-PMI algorithm was applied to construct a domain-specific dictionary, ultimately integrating 5,739 positive sentiment words and 7,170 negative sentiment words. TF-IDF was used to generate seed candidate words, with the output limited to 500 key words, from which we selected 50 positive and 50 negative seed words (Table S1). Through sentiment classification on the basis of the sentiment dictionary, each question was categorized, and its sentiment value was obtained. The proportion of sentiment classification over different times is depicted in Figure 5, which shows that the proportion of positive sentiment is slightly greater than that of negative sentiment. However, the overall trend in sentiment classification remains relatively stable over time.

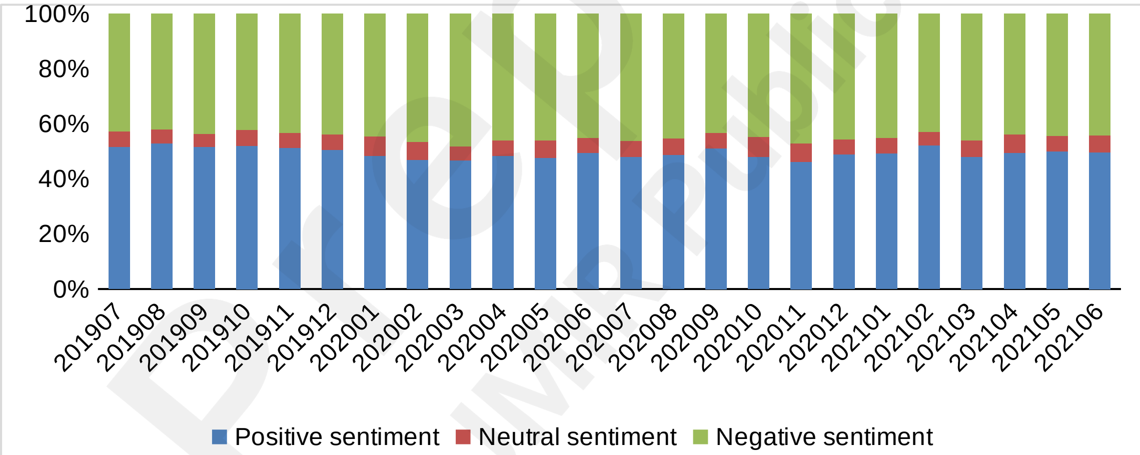

Figure 5 Emotional map for different dates

Regression prediction based on the LightGBM model

This study focuses on samples after thematic clustering and removal of noise points, comprising a total of 64,237 data entries. For each question, corresponding thematic and sentiment category labels were obtained through thematic clustering and sentiment classification. The selected variables include the question's theme, sentiment category, sentiment score, title length, content length, posting year, posting month, posting date, public holiday status, time of day, day of week, and view count, with the number of responses as the dependent variable. A description of the features can be found in Table 1.

Table 1 Feature description

Feature	Feature description	Numerical classification

Topic	The topic of the content; 0=work; 1=love; 2=depression; 3=boyfriends or girlfriends; 4=school; 5=marriage; 6=family	Categorical variable
Emotional category	0=positive; 1=neutral; 2=negative	Categorical variable
Emotional score	The logarithm of the absolute value plus 1	Continuous variable
Page view	The logarithm of the number of page views posted on a given date	Continuous variable
Year	Year of the post	Categorical variable
Month	Month of the post	Categorical variable
Day	Day of the post	Categorical variable
Topic length	The logarithm of the number of words in the post title	Continuous variable
Content length	The logarithm of the number of words in the post content	Continuous variable
Hour	0=00:00~00:59, 1=01:00~01:59, 2=02:00~02:59, 3=03:00~03:59, 4=04:00~04:59, 5=05:00~05:59, 6=06:00~06:59, 7=07:00~07:59, 8=08:00~08:59, 9=09:00~09:59, 10=10:00~10:59, 11=11:00~11:59, 12=12:00~12:59, 13=13:00~13:59, 14=14:00~14:59, 15=15:00~15:59, 16=16:00~16:59, 17=17:00~17:59, 18=18:00~18:59, 19=19:00~19:59, 20=20:00~20:59, 21=21:00~21:59, 22=22:00~22:59, 23=23:00~23:59	Categorical variable
Week	0=Monday; 1=Tuesday; 2=Wednesday; 3=Thursday, 4=Friday; 5=Saturday; 6=Sunday	Categorical variable
Holiday	0=no; 1=yes	Categorical variable
Reply quantity	The logarithm of the number of replies to the post	Continuous variable

We conducted a statistical description of the selected variables, excluding the temporal characteristics of the posts. The details can be found in Table 2.

Table 2 Feature characteristics

Feature/Category	N	Mean±SD/Percentage
Page view	64237	6.12±0.44
Sentiment category		
Positive	31867	49.60
Neutral	3744	5.80

Negative	28626	44.60
Sentiment score	64237	1.80±1.05
Topic		
Work	3638	5.70
Love	1723	2.70
Depression	28811	44.90
Boyfriends or girlfriends	6496	10.10
School	10969	17.10
Marriage	4793	7.50
Family	7807	12.20
Title length	64237	2.75±0.51
Content length	64237	4.40±1.09
Reply quantity	64237	1.00±0.76

Model interpretability

Global interpretability

The global interpretation graph of LightGBM, shown in Figure 6, presents SHAP values with 0 as the dividing line. The left side represents features with SHAP values less than 0, and the right side represents features with SHAP values greater than 0. The graph indicates that the view count has a positive effect on the response volume. Most other features are categorical variables, and their impact is not clearly discernible from the graph. The average SHAP value for each feature is detailed in the Appendix.

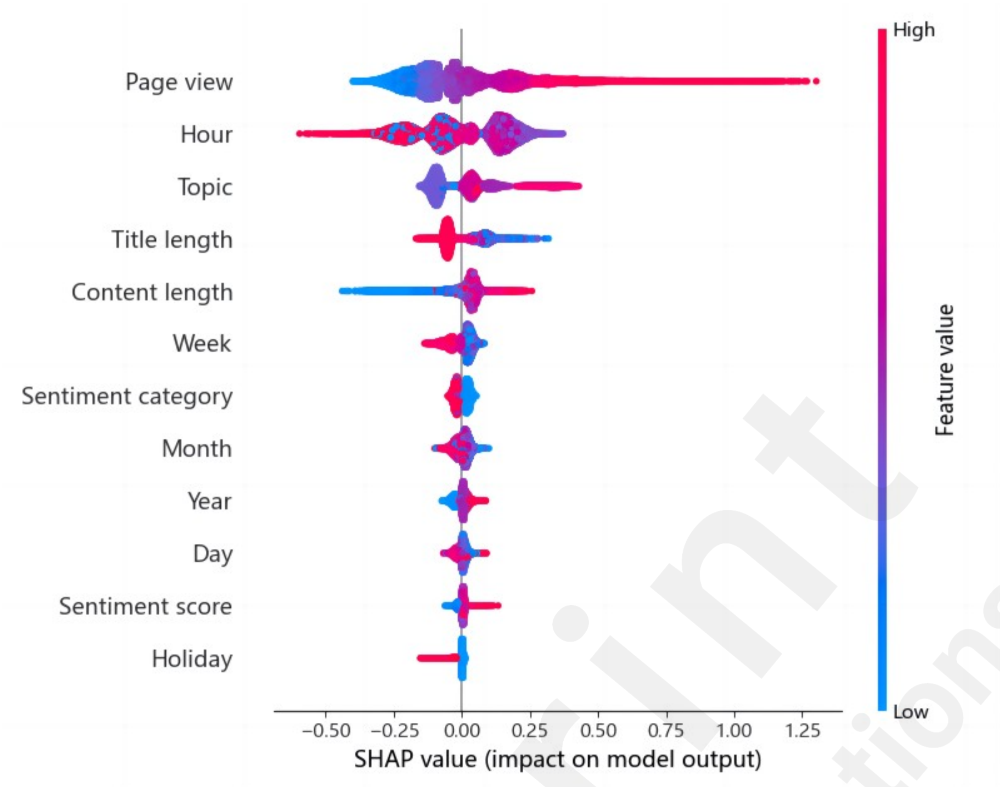

Figure 2 SHAP values for all the features

Local interpretability

Since feature values represent categories without a clear magnitude, a feature-SHAP value scatter plot is constructed for each feature to analyze its impact on the response volume.

The impact of thematic features on responses volume is illustrated in Figure 7. Themes 1 and 2, which correspond to love and depressive moods, respectively, exhibit SHAP values less than 0, whereas Themes 3 and 5, which correspond to relationships and marriage, respectively, have SHAP values greater than 0. This finding indicates that topics related to love and depressive moods have a negative effect on response volume, whereas topics related to relationships and marriage have a positive effect. The impact of other themes on response volume is not clearly defined.

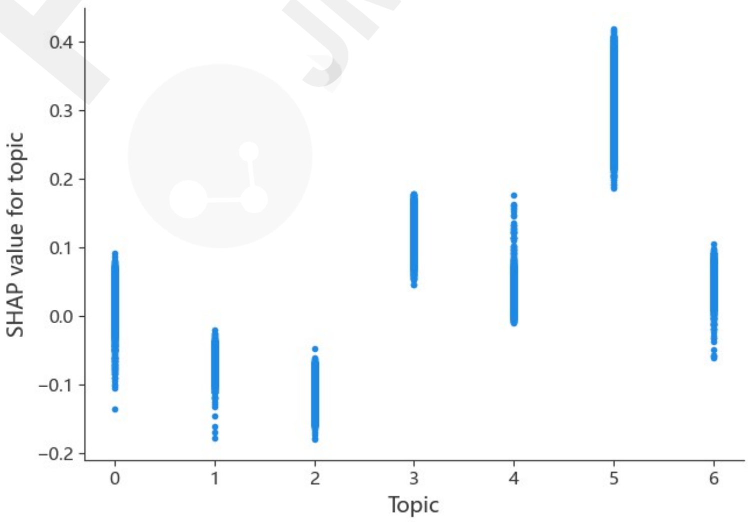

Figure 3 SHAP values for different topics. Topic description is provided in Table 1.

The impact of emotional features on the response volume is shown in Figures 8 and 9. When the sentiment category is positive, the SHAP value is greater than 0; conversely, when the sentiment category is neutral or negative, the SHAP value is less than 0. This finding indicates that positive emotions have a positive effect on the response volume, whereas neutral and negative emotions have a negative effect. Positive emotions may be easier for psychologists to provide advice on, whereas psychologists tend to respond more cautiously to neutral or negative emotions, hence negatively impacting response volume. The impact of the sentiment score on response volume is not clearly defined.

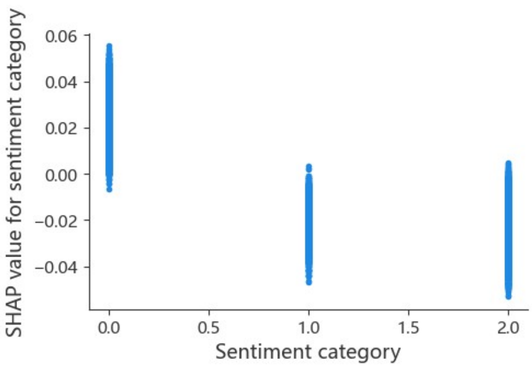

Figure 4 SHAP value for different sentiment categories

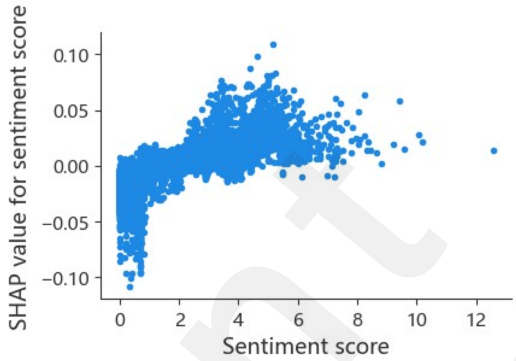

Figure 5 SHAP value for sentiment scores

The impacts of other post features on response volume are shown in Figures 10 to 18. The results indicate that when page views exceed 6.1, corresponding to more than 445 views, and the title length is less than 2.95, equivalent to less than 20 characters, the SHAP value is greater than 0. Similarly, when the content length exceeds 4.1, equivalent to more than 60 characters, and posts are made between 5 am to 5 pm, from Monday to Thursday, and on nonpublic holidays, the SHAP value is greater than 0, suggesting a positive effect on the response volume. Conversely, when page views are less than 6.1, i.e., fewer than 445 views, and the title length exceeds 2.95, i.e., 20 characters or more, response volume appears to be lower. Additionally, when the content length is less than 3.14, i.e., fewer than 23 characters, and posts occur at the end of the month (20th–26th), from 9 pm to midnight, on weekends, or public holidays, the SHAP value is less than 0, indicating a suppressive effect on response volume. The impacts of year and month on response volume are not clearly defined.

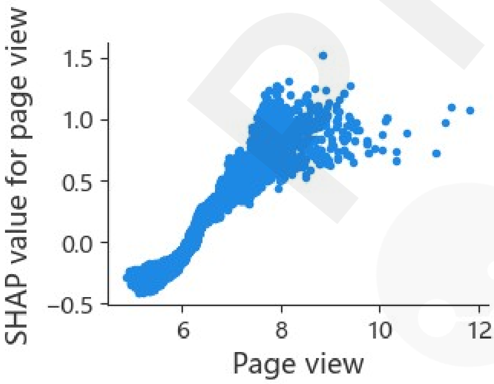

Figure 6 SHAP values for different page views

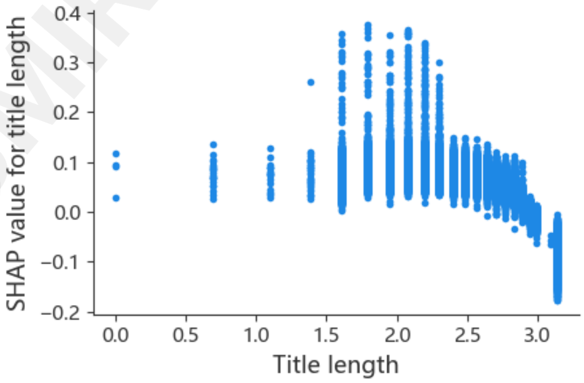

Figure 7 SHAP values for different title length

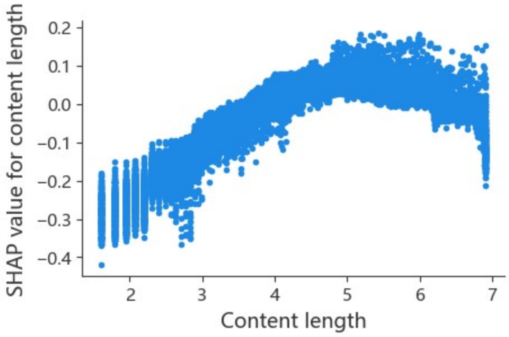

Figure 8 SHAP values for different content length

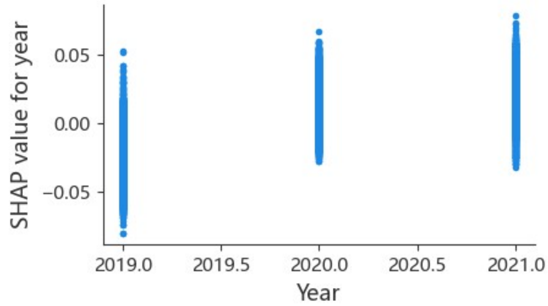

Figure 9 SHAP values for different year

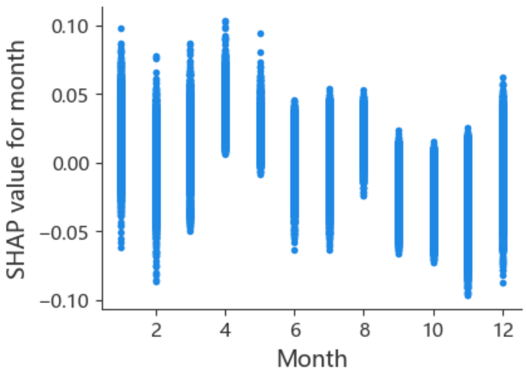

Figure 10 SHAP values for different month

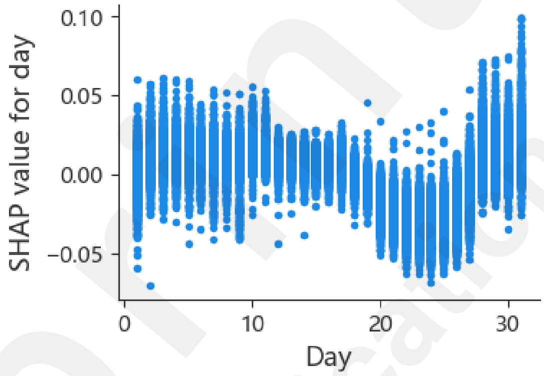

Figure 11 SHAP values for days in a month

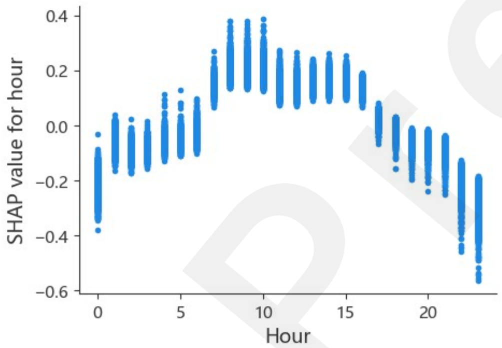

Figure 12 SHAP values for hours in a day

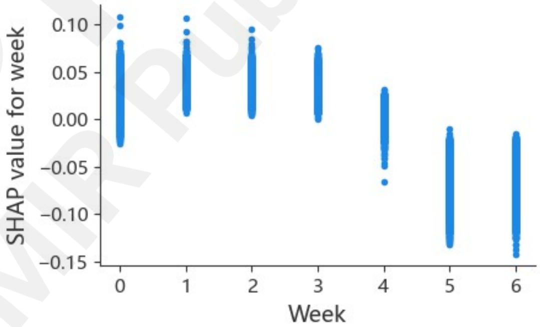

Figure 13 SHAP values for days in a week

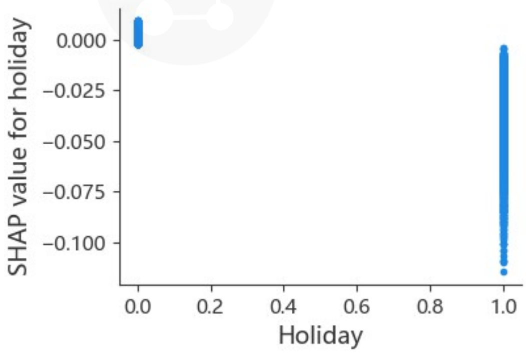

Figure 14 SHAP values for holiday

Discussion

Principal findings

This paper presents thematic and sentiment analyses on the content in the public welfare Q&A section of the Yi Dian Ling online mental health community, identifying seven themes: work, love, depressive moods, relationships, school, marriage, and family. Through simple statistical analysis, changes in themes of interest to users with mental health needs are identified, and posts are classified according to sentiment using a sentiment dictionary, assigning each post thematic and sentiment category labels. The results indicate that, the demand for psychological services focus primarily on these seven aspects. Platforms and professionals focusing on mental health should be attentive to shifts in users' psychological service needs and respond in a timely manner. Platforms should also adjust the allocation of psychological resources and promotional strategies to enhance service quality and attract more user participation. Additionally, platforms can categorize question content by theme and sentiment, aiding professionals in providing precise services to users in need and enabling general users to more conveniently locate and engage with topics of interest.

Furthermore, the predictions and SHAP value interpretations of response volume indicate that the themes "Relationships" and "Marriage" have a positive impact on response volume, whereas "Love" and "Depressive Moods" have a negative impact. Positive emotions have positive effects, whereas neutral and negative emotions have negative effects. Post characteristics such as view count, title length, content length, posting hour, day of week, and public holiday status have varying degrees of impact on response volume. Therefore, platforms should prioritize improving service levels and enhancing their reputation to attract more users and increase view counts, thereby increasing response rates. For themes with negative impacts, platforms should intensify attention and consider implementing point-based incentives for professionals responding to these topics. Accumulated points could be converted into rewards to incentivize active engagement. Additionally, attention should be directed toward the distribution of psychologists, stabilizing and adjusting staff structures, and establishing a reward system to motivate psychologists and other users with service needs to contribute knowledge, ultimately fostering increased response volume and community engagement.

Research implications

Theoretical implications

This study involves thematic and sentiment analyses of post content, selecting thematic features, emotional features, and other characteristics of posts as influencing factors. The LightGBM algorithm is used for predictive modeling, and the SHAP method is applied to interpret the model. In addition, the impact of various factors on response volume is analyzed through feature-SHAP value scatter plots. This approach not only expands the methodology of related theoretical research but also provides analytical insights for future studies, promoting the application of explainable machine learning in the fields of online health and mental health.

Practical implications

First, through thematic and sentiment analysis, a deeper understanding of users' needs and focal points in online mental health communities can be achieved. This enables precisely identifying issues and topics, predicting trends in users' emotional development, and thereby providing resources and emotional support that align with users' expectations. Moreover, thematic and sentiment analysis can also reveal the main issues and potential needs of users within the community. This information is valuable for identifying new research directions, conducting social psychological surveys, and developing related policies.

Second, by analyzing the factors influencing response volume in the Yi Dian Ling online mental health community as a case study, targeted suggestions and measures can be proposed to stimulate response volume. These insights contribute to a more rational allocation of resources among mental health professionals across various fields. An increase in response volume also enables individuals seeking psychological services to access more information, thereby increasing the likelihood of addressing mental health concerns and fostering greater user engagement across various user demographics.

Conclusion

This study employs explainable machine learning methods to investigate the factors influencing response volume in online mental health communities. It identifies critical factors affecting response volume in these communities, reveals the extent to which different features impact response volume, and offers relevant suggestions. These findings can provide community managers with targeted optimization strategies to increase both the volume and quality of responses in online mental health communities. Additionally, our findings can assist OHC managers in providing more relevant and effective mental health education and support, promoting the dissemination of mental health knowledge, and improving mental health awareness and literacy. Despite its contributions, this study has several limitations. First, the selection of candidate positive and negative sentiment words was based on PMI values and personal subjective experience, potentially introducing subjective biases into sentiment classification. Second, the study considers only the impact of post content and characteristics on response volume, overlooking other factors such as user characteristics, the professional level of psychologists, and the development status of the platform. Finally, in the LightGBM model predictions, the R-squared value reached only 0.238, indicating that the model's fit is only moderately effective. Future studies should assess the effectiveness of various sentiment analysis models to choose the most accurate method. When influencing factors are analyzed, a multifaceted approach should be adopted to explore characteristics that impact response volume, thereby exploring the effects of other features on response volume.

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Conflicts of interest

All the authors declare that they have no conflicts of interest.

Abbreviations

BERT: bidirectional encoder representations from transformers
CMHS: China Mental Health Survey
LightGBM: light gradient boosting machine
OHC: online health community
SHAP: shapley additive explanations
SO-PMI: semantic orientation–pointwise mutual information
TF-IDF: term frequency-inverse document frequency

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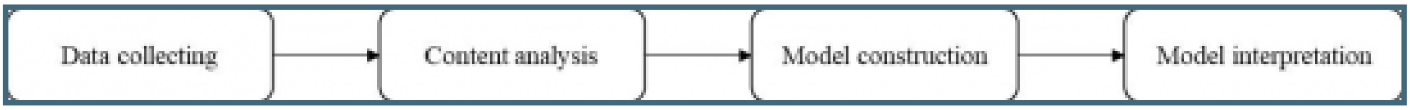
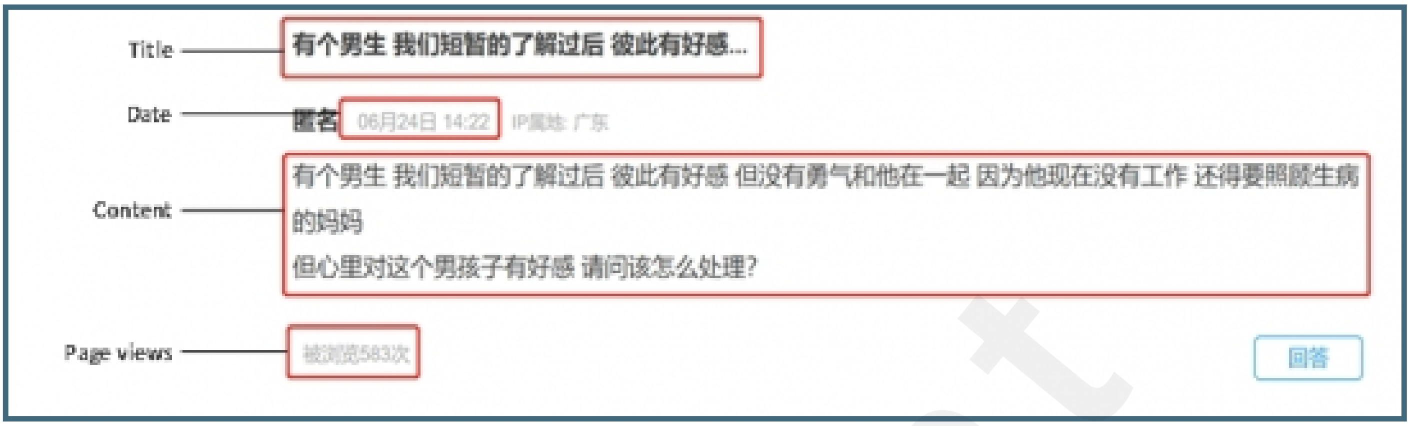
Supplementary Files

Figures

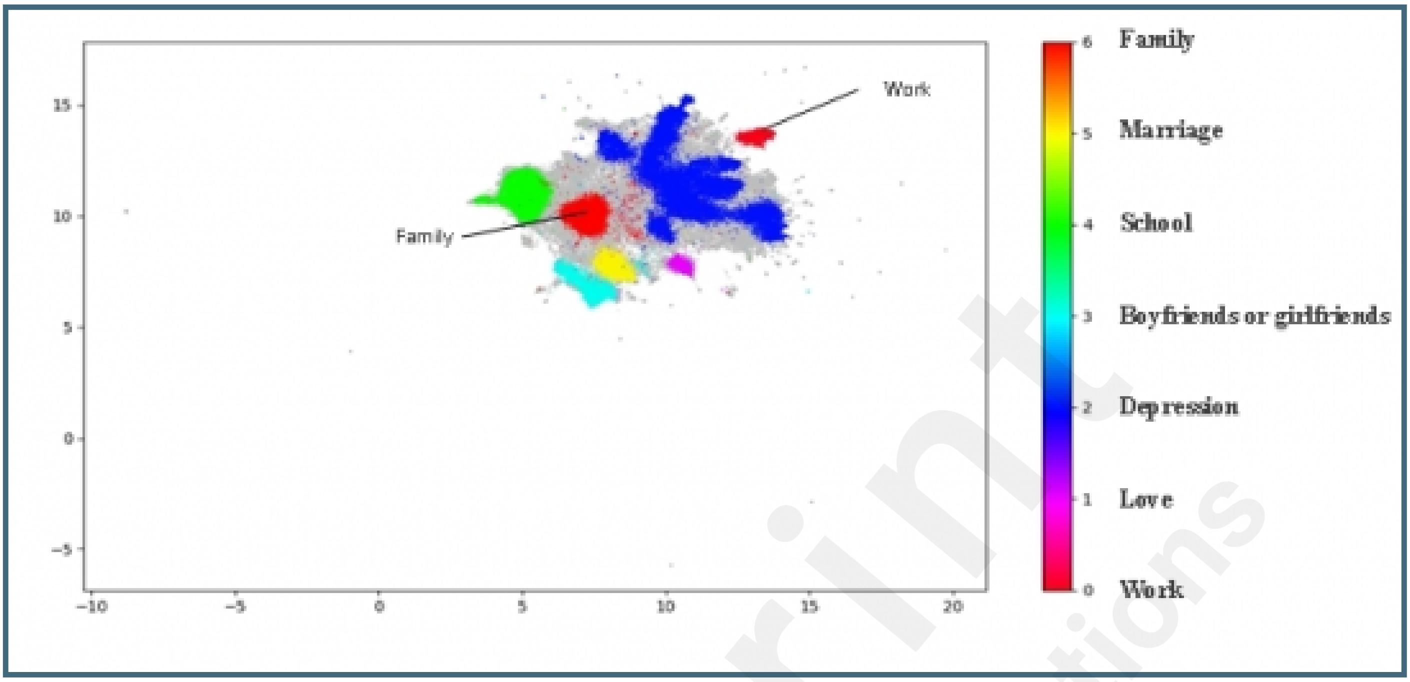
Data analysis road map.



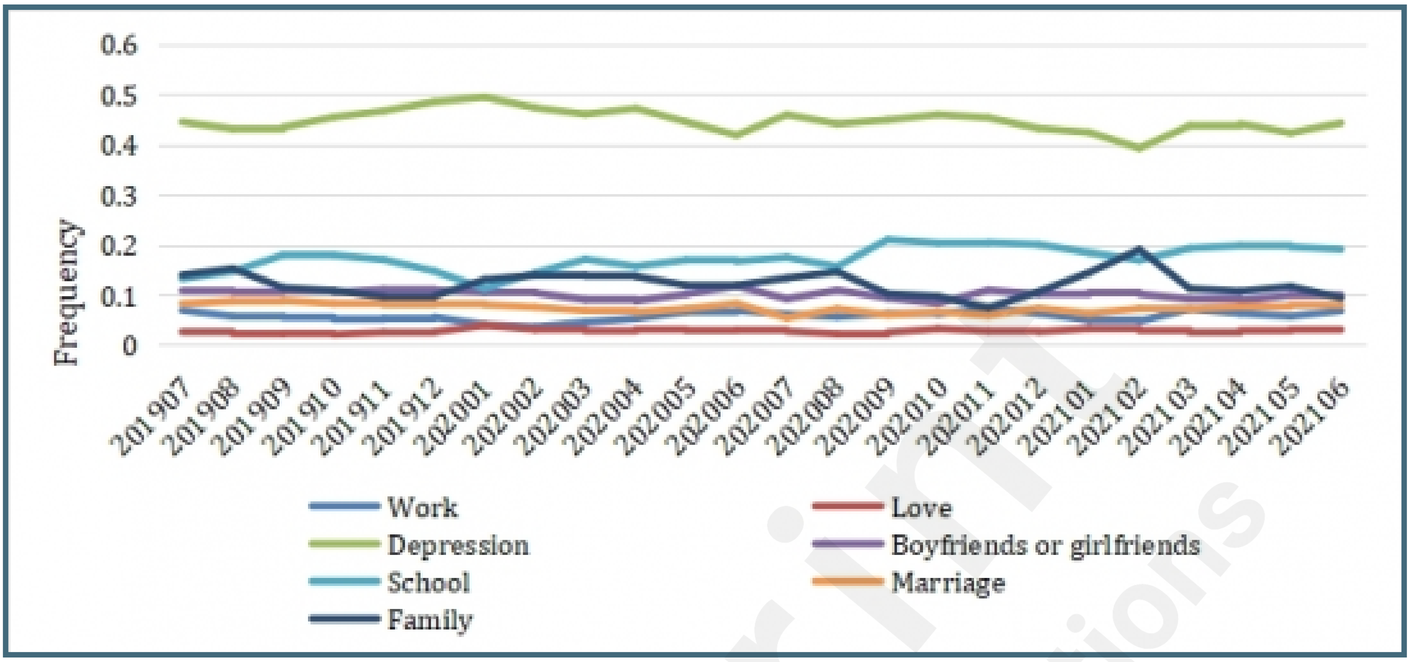
Example of extracted features for the post.



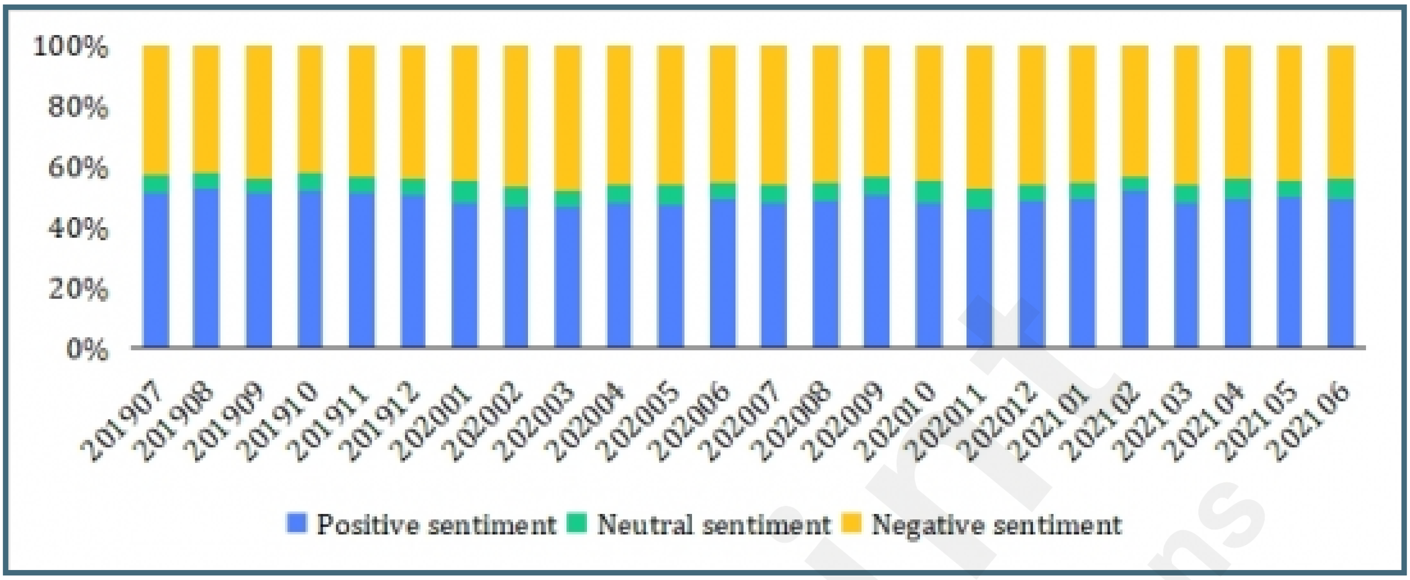
Topic clustering results.



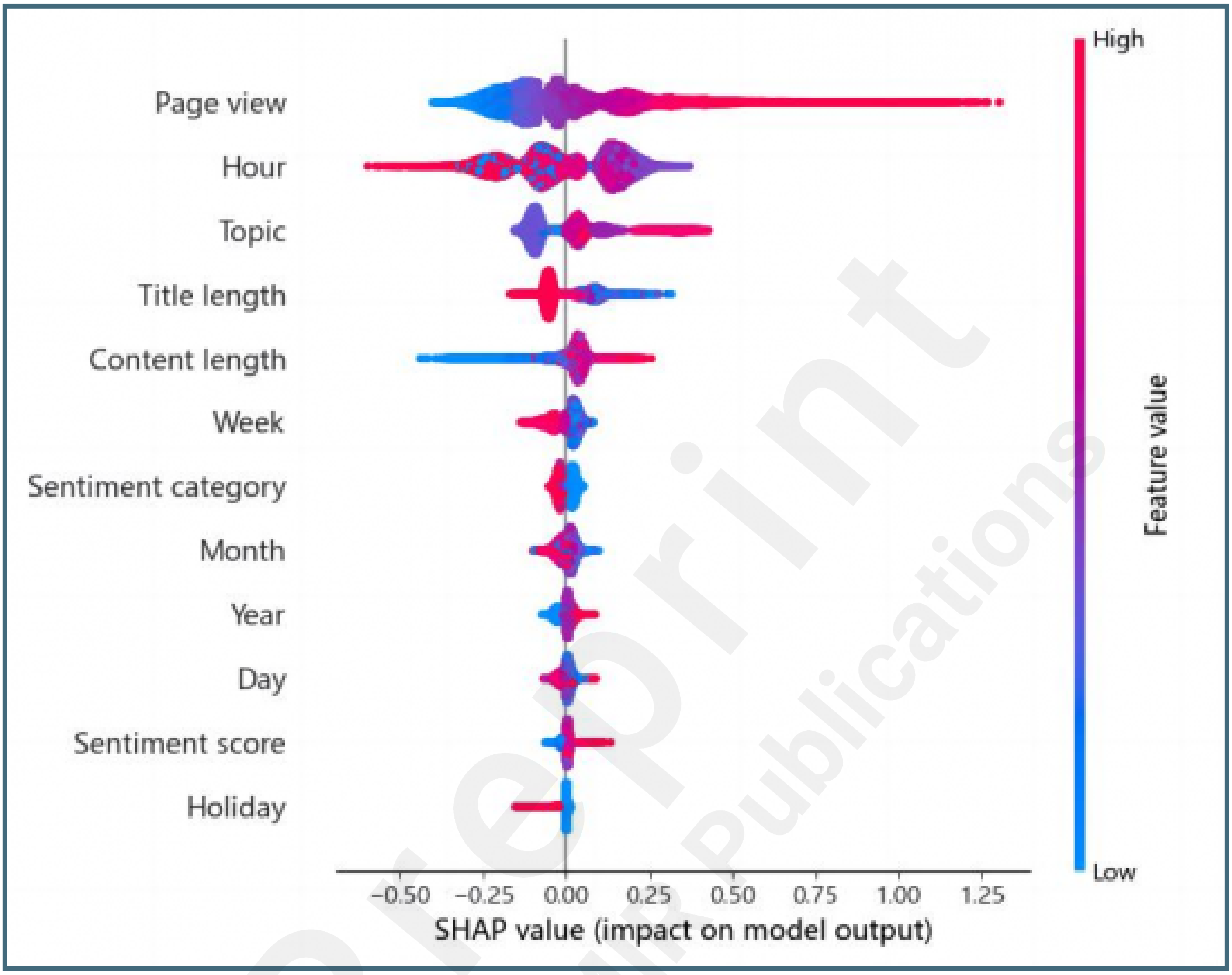
Topic frequency evolution.



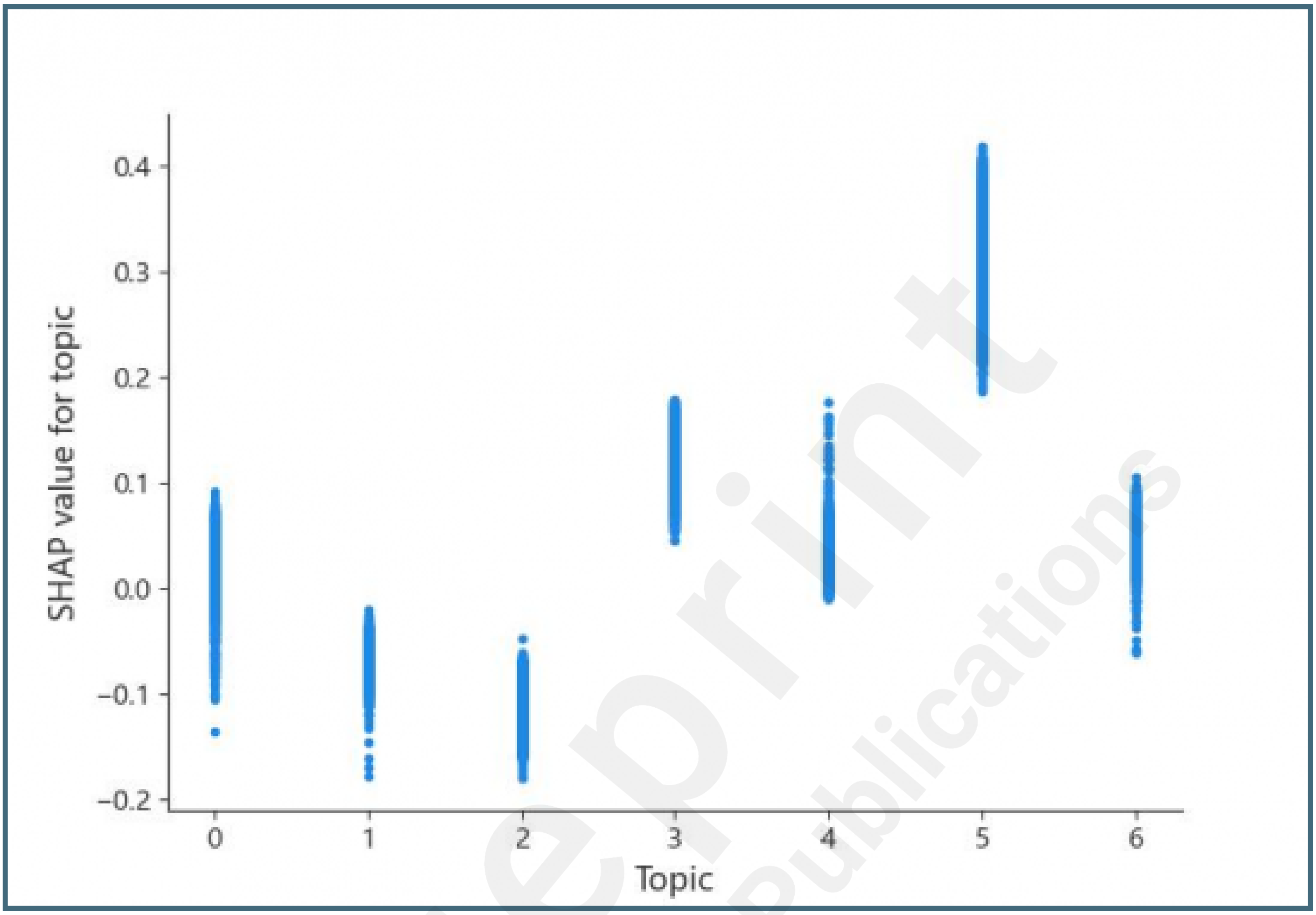
Emotional map for different dates.



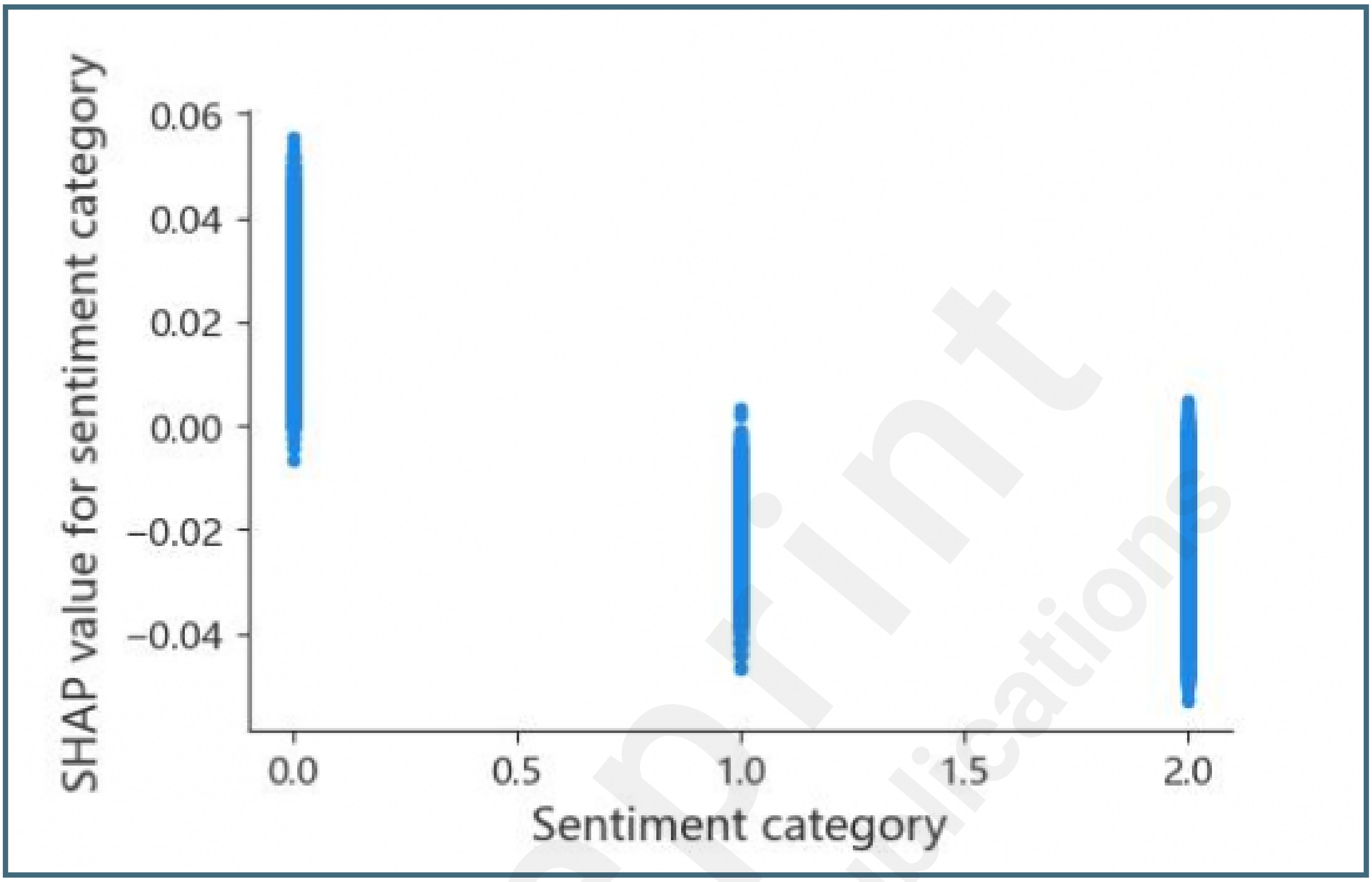
SHAP values for all the features.



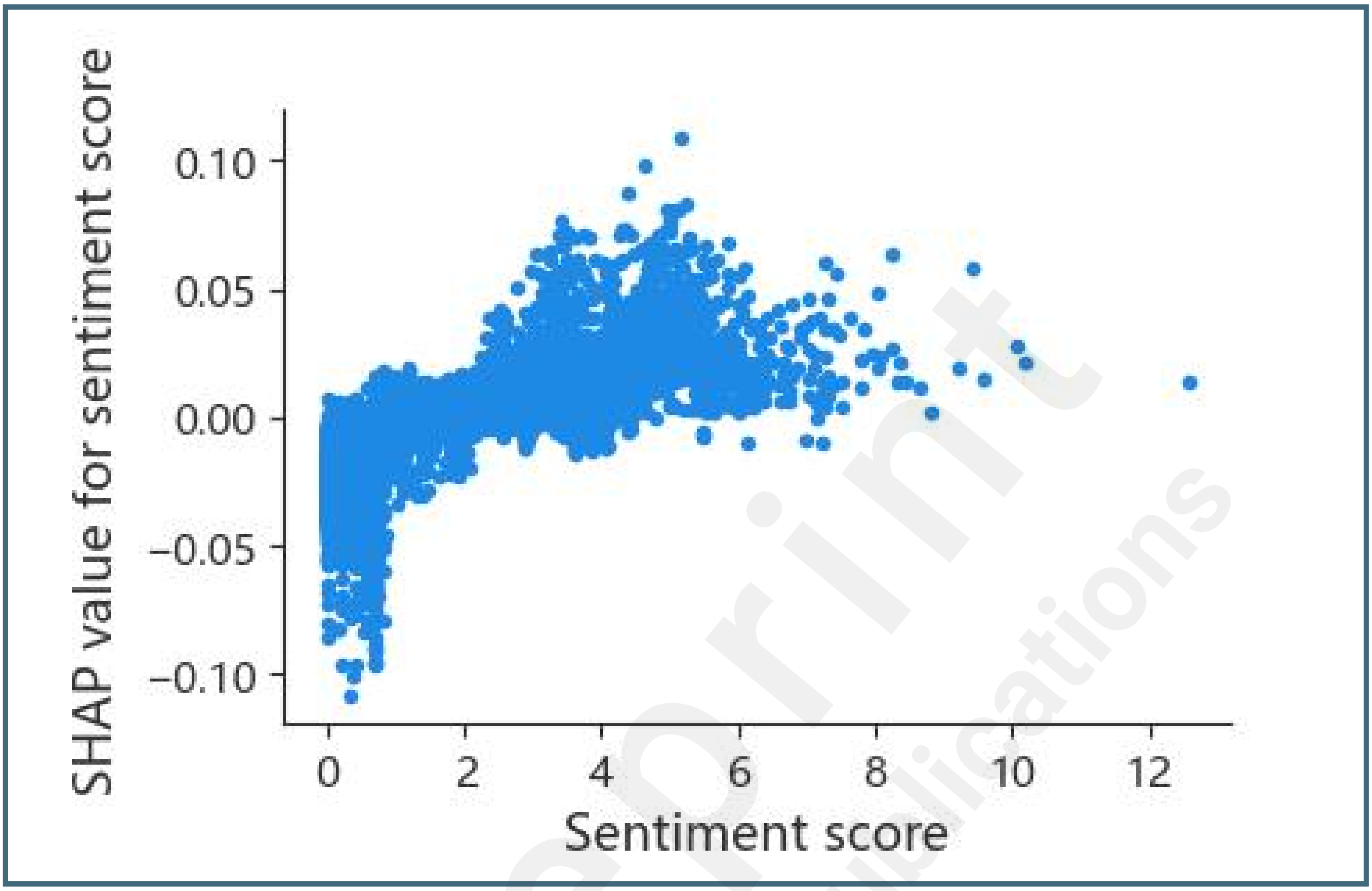
SHAP values for different topics.



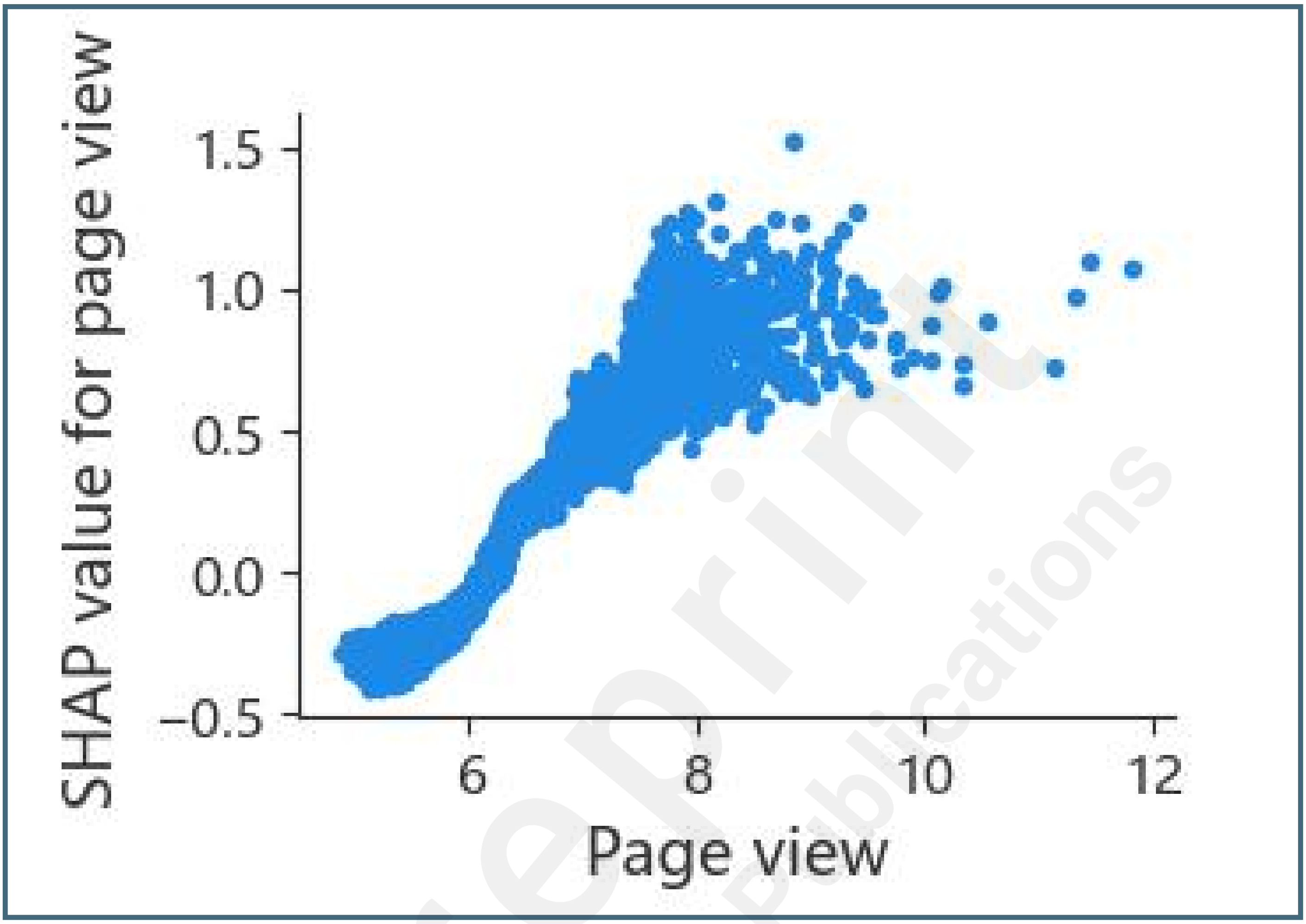
SHAP value for different sentiment categories.



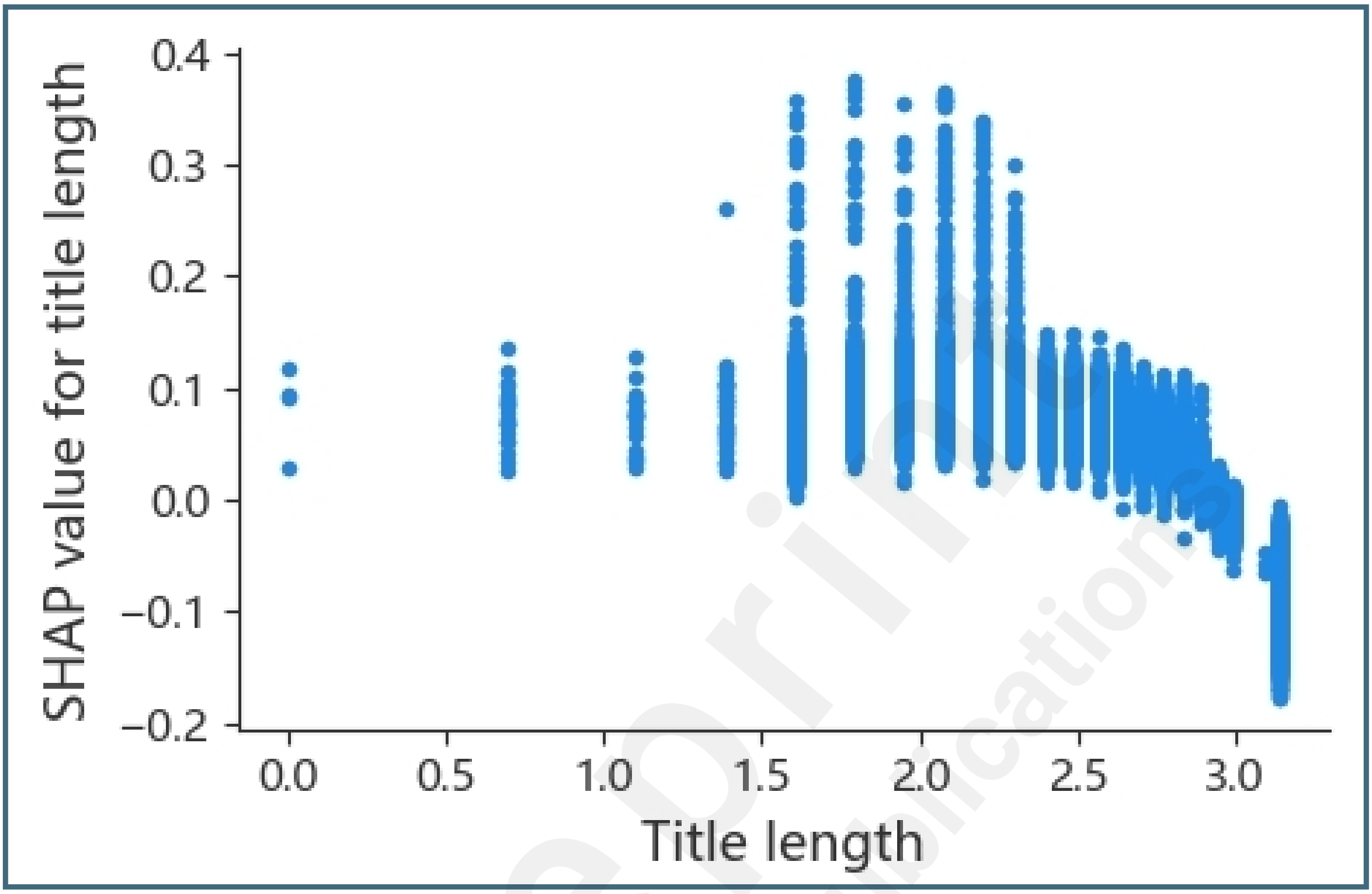
SHAP value for sentiment scores.



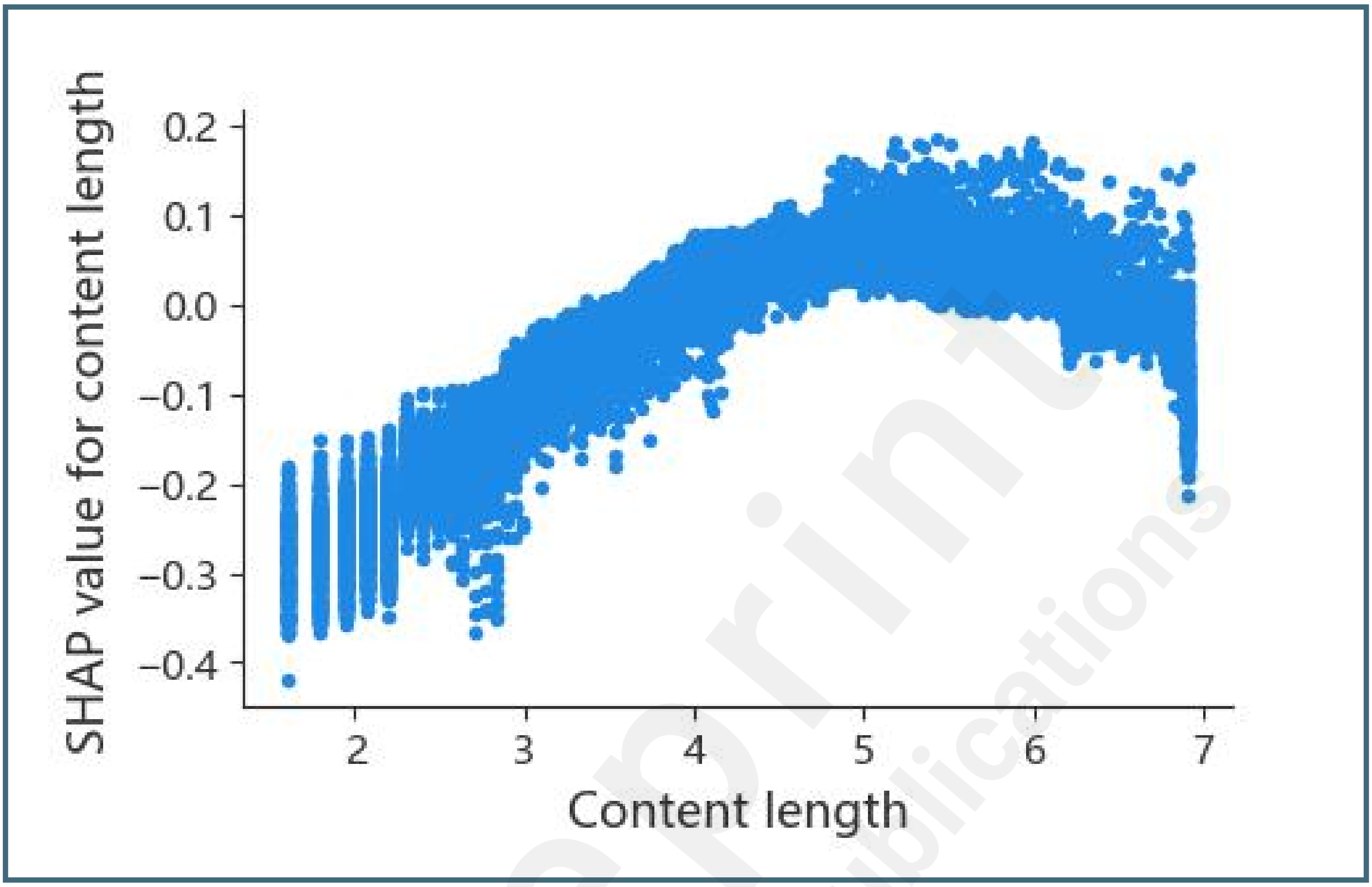
SHAP values for different page views.



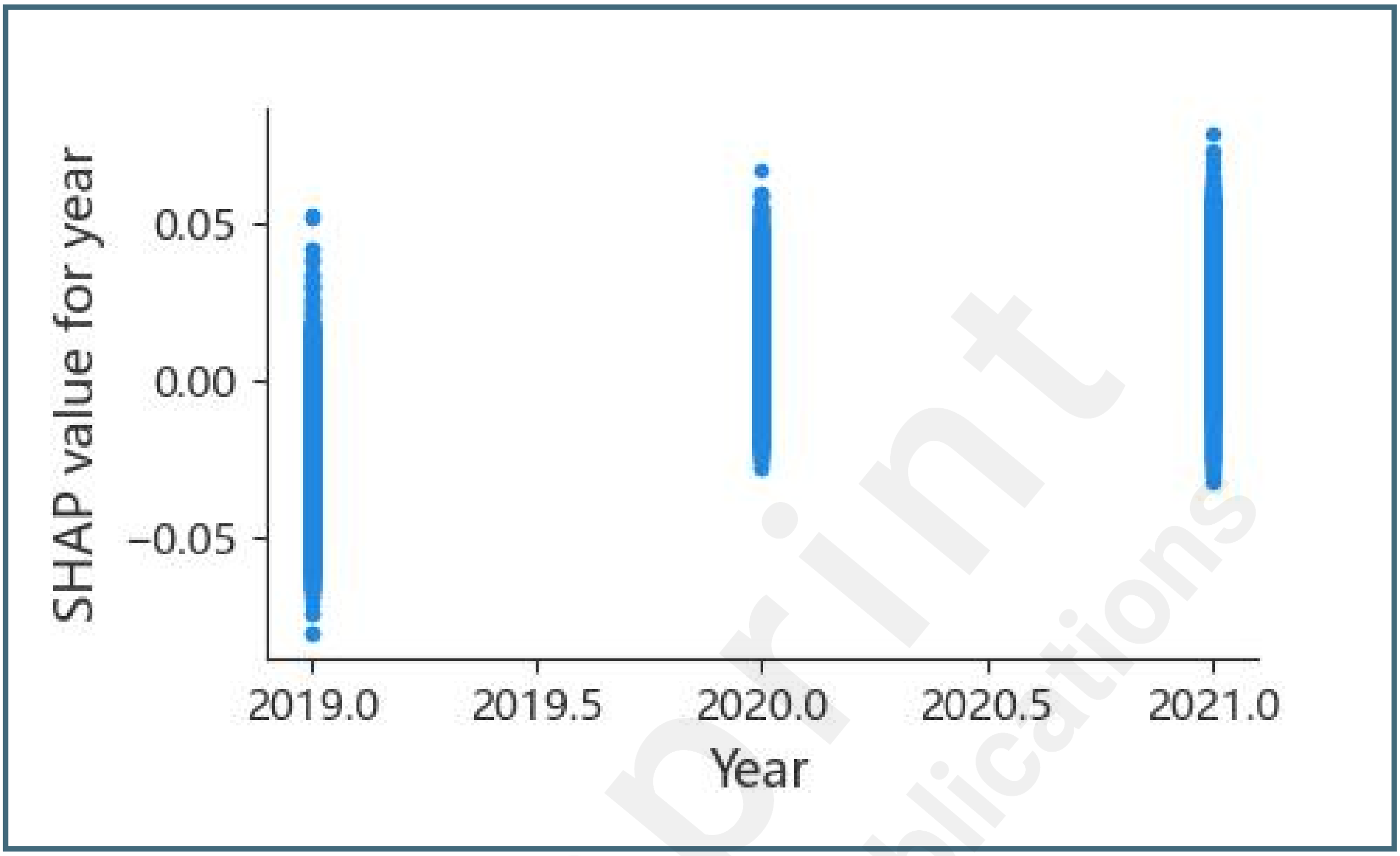
SHAP values for different title length.



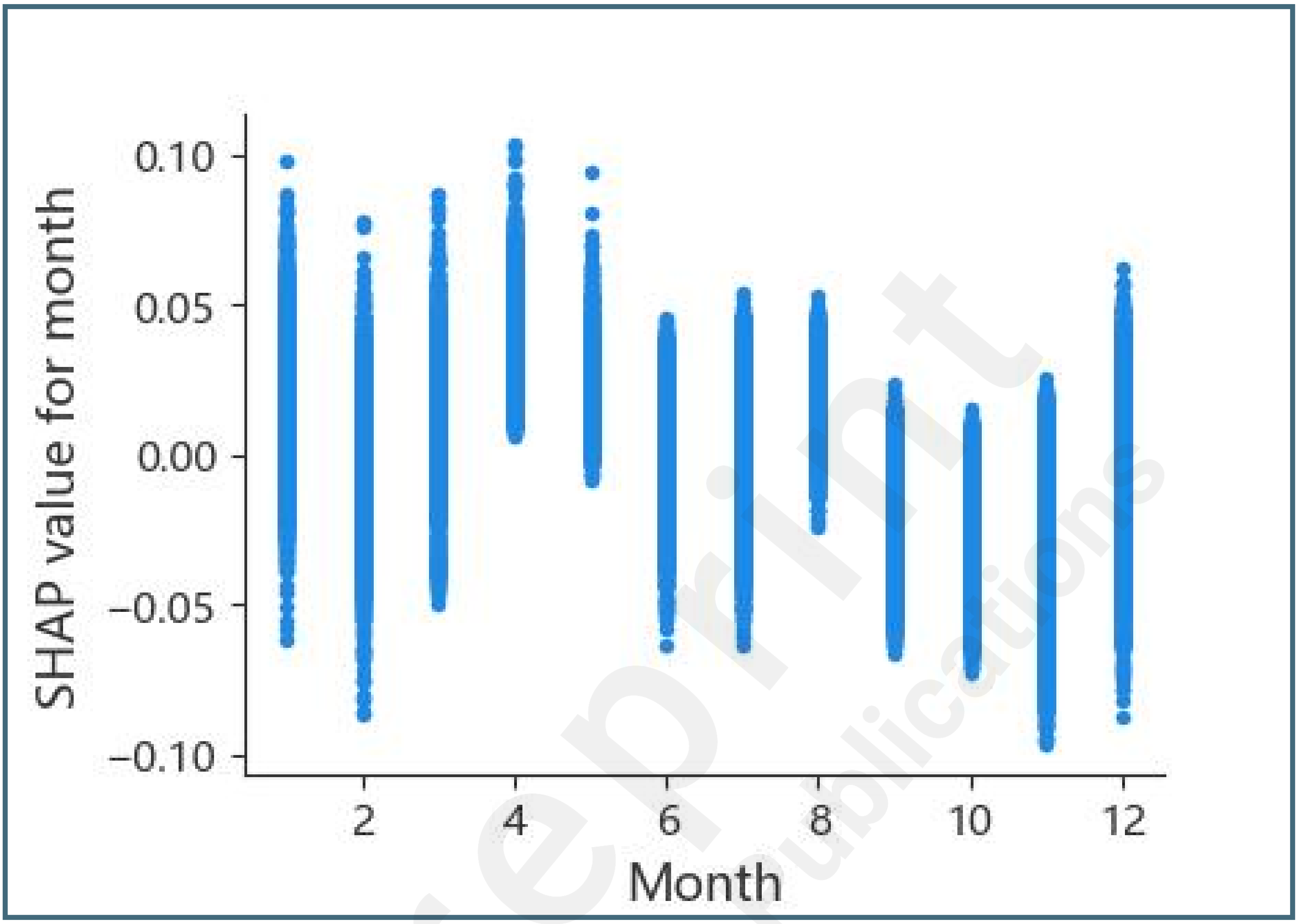
SHAP values for different content length.



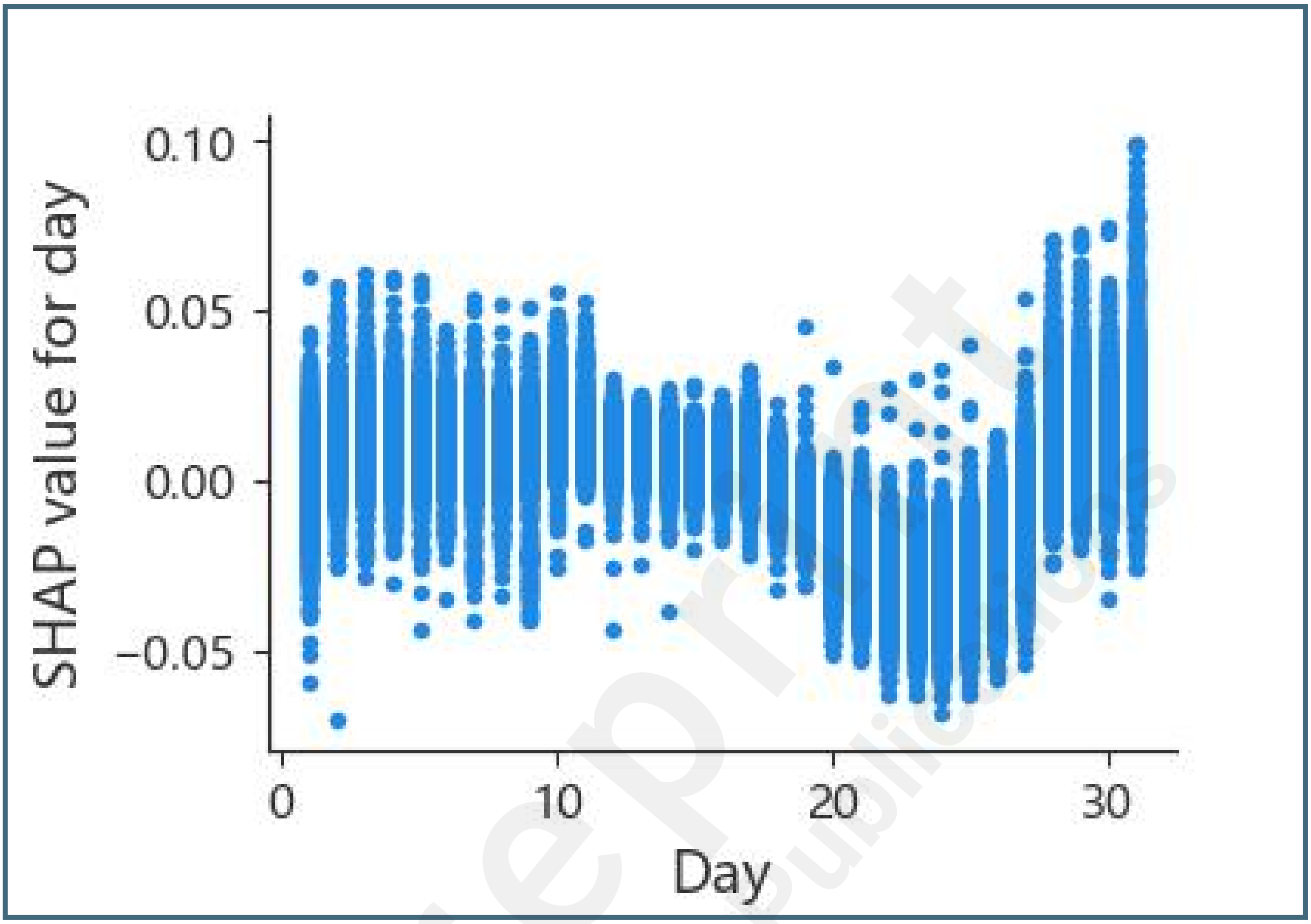
SHAP values for different year .



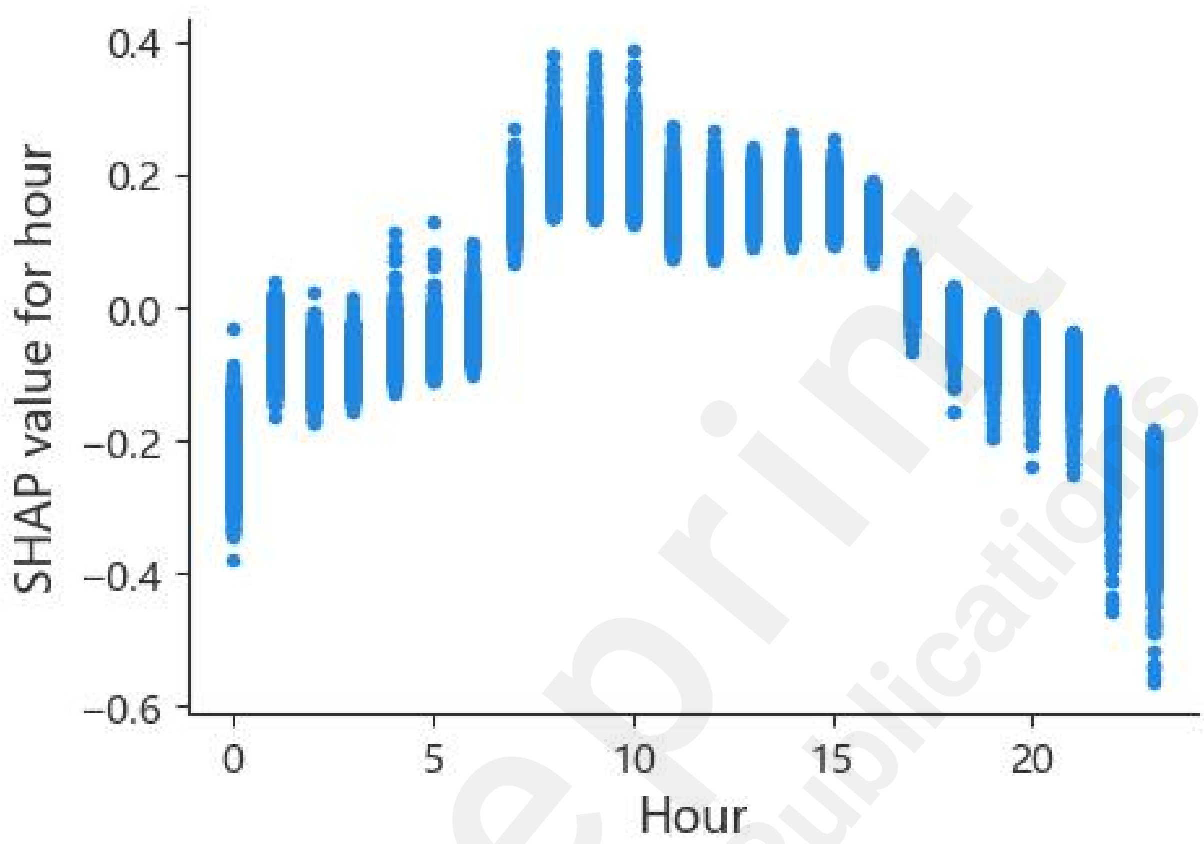
SHAP values for different month.



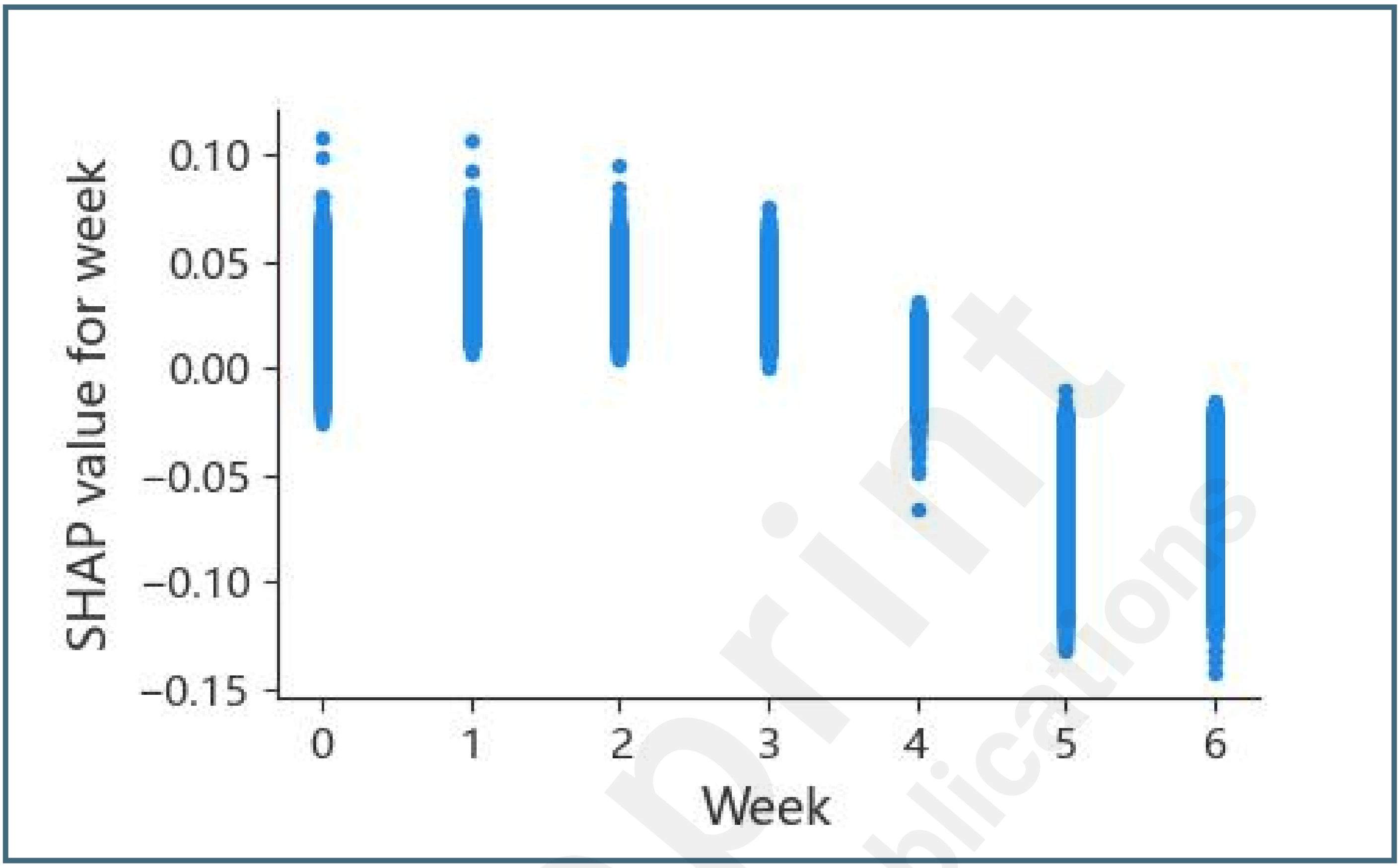
SHAP values for days in a month.



SHAP values for hours in a day.



SHAP values for days in a week.



SHAP values for holiday.