

Analysis of Behavioral Facilitation Information During Disasters Based on Reader Attributes and Personality Traits

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During disasters, a large volume of messages are posted on social networking services (SNS). Some of these messages contain behavioral facilitation information, which either encourages or discourages specific actions. However, the interpretation of such information depends on the personality traits of the individuals affected. In this study, we hypothesize that victims' personality traits influence their perception of behavioral facilitation information, and we analyze the characteristics of these differences. Focusing on typhoons, we propose a method for extracting behavioral facilitation information from posts on X (formerly Twitter) during typhoon-related disasters. The extracted information is then classified into four content-based categories: suggest, inhibition, encouragement, and wish. Furthermore, we categorize individual personality traits into five dimensions (the Big Five), and also take into account their age and sex. We then analyze how the perception of each type of behavioral facilitation information varies according to these traits. Our analysis reveals that, during disasters, the interpretation of behavioral facilitation information exhibits distinct and consistent patterns depending on the personality traits of the victims.

Povzetek: Razvili so razširjen in razločljiv sistem Cardio Care za računalniško analizo EKG. Preverili so modele ViT, DeiT in BEiT – najboljši je ViT. Dodali so Grad-CAM za vizualna pojasnila, sistem pa deluje tudi z mobilnimi fotografijami papirnih EKG-jev.

1 Introduction

In recent years, we have seen an increase in the frequency of large-scale natural disasters, including typhoons, heavy rainfall, and earthquakes, affecting wide areas. During these disasters, it is critical to promptly provide accurate and essential information to those affected. Currently, many people use social networking services (SNS) to share and access disaster-related information. On these platforms, not only general users and disaster victims but also local governments and other government agencies are proactively sharing information[1]. Among many messages posted on SNS during disasters, a significant number include instructions such as “Please evacuate” or “Keep away from the river.” These messages are intended to encourage or discourage certain behaviors and are known to have a significant impact on people’s evacuation decisions. In this study, we refer to such content as “behavioral facilitation information” (hereinafter “BF information”).

Our previous research has focused on extracting the BF information from SNS with the goal of influencing readers’ actions[2][3][4]. BF information can change and may encourage or discourage certain behaviors. Here, we propose a method to automatically extract BF information from

large amounts of disaster-related SNS content and classify it into four types based on its communicative intent: “Suggest,” “Inhibition,” “Encouragement,” and “Wish.” We collectively refer to these four categories as BF information types. While BF information can be effective in guiding disaster victims, it can also have unintended or counterproductive effects. For example, Kimura¹ notes that a message like “The river is overflowing and dangerous, so please stay away” might lead most people to avoid the area out of fear. However, some individuals—driven by strong curiosity or a sense of responsibility—might feel compelled to move toward the danger to observe the situation, acting against the message’s intent. This suggests that the same information can be interpreted differently depending on readers’ personality traits, potentially leading to adverse outcomes.

Based on these observations, we hypothesize that individual personality traits influence how BF information is perceived during disasters. This study, therefore, analyzes the relationship between different types of BF information and the reader’s personality characteristics. For personality modeling, we adopt the Big Five personality framework. This framework is a widely recognized and fundamental model in psychology for understanding human

¹<https://president.jp/articles/-/71423>

personality, describing it across five key dimensions: “Extraversion,” “Agreeableness,” “Conscientiousness,” “Neuroticism,” and “Openness.” We use these five factors as the reader’s personality traits in our analysis. This study specifically focuses on disasters caused by typhoons, and we use X (formerly Twitter) as our target SNS platform for information sharing and analysis.

The main contributions of this study are:

- A method for extracting BF information and classifying it into four BF information types.
- An analysis of how each BF information type influences readers based on their different personality traits.

These contributions will help develop systems that can deliver more effective, disaster-related information, tailored to the unique personality traits of each individual victim.

2 Related work

Numerous studies have been conducted on extracting important information from social networking services (SNS) during disasters. Xiaodong et al. [5] focused on the linguistic, sentimental, and emotional characteristics unique to messages on SNS and proposed a model that classifies tweets into disaster-related and non-disaster-related categories. Paul et al. [6] analyzed tweets related to typhoons that occurred between 2012 and 2018 and applied BERT to classify tweets regarding power outages and communication failures into specific categories. Yasin et al. [7] employed machine learning methods to classify disaster-related tweets into six labels—“Need rescue,” “Disabled persons, elderly, children, women,” “Need water,” “Injury,” “Illness,” and “Flooding”—to identify the information necessary to assist the tweet authors. These studies have categorized disaster or damage information, such as “Rescue,” “Donation,” and “Tsunami,” into topic-specific categories. In contrast, our study differs in that it focuses on classifying and analyzing BF information that facilitates or discourages specific actions.

Research focusing on personality traits about disaster-related information has also been conducted. Gupta et al. [8] analyzed human behavior during evacuation by focusing on personality traits to predict traffic conditions during disasters, demonstrating that evacuation behaviors differ depending on individual personality traits. While this study is similar to ours in that it analyzes differences in reactions based on personality traits, our work differs in that it targets reactions to behavioral facilitation information during disasters explicitly.

In addition, many studies have analyzed tweets during disasters. Roy et al. [9] analyzed follower counts and activity patterns of readers during hurricanes, showing that those who provide effective information during disasters are not solely determined by their posting frequency. Lu et al. [10] analyzed deleted tweets and demonstrated that

non-effective content can be classified into ten categories. David et al. [11] classified tweets into 11 categories, such as “Need help” and “Looking for someone,” and conducted sentiment analysis, showing that tweets during disasters mainly consist of support or suggestion messages. Yamada et al. [12] analyzed tweets during the 2018 Western Japan heavy rain disaster, focusing on the number of tweets over time, the use of hashtags and emojis, the number of retweets, and the number of tweets containing news article URLs. Nishikawa et al. [13] analyzed the content and trends of tweets tagged with rescue-request hashtags posted during the 2018 Western Japan heavy rain disaster. These studies analyzed tweets with a focus on aspects such as tweet frequency, hashtags, keywords, and sentiment. In contrast, our study differs in that it classifies tweets by type of behavioral facilitation information and analyzes them with a focus on the personality traits of the readers.

3 Extraction of behavioral facilitation information

3.1 Target scope of behavioral facilitation information

In this study, we define BF information as content that explicitly urges or discourages others from taking specific actions. We have excluded tweets that imply certain behaviors without direct language. For example, the sentence, “This typhoon has very strong winds, so let’s bring the flower pots indoors before it arrives,” explicitly encourages people to bring flower pots indoors. Therefore, we classify it as BF information. In contrast, a sentence like, “The wind is really strong with this typhoon—what would happen if someone went outside today?” implies a cautionary tweet. However, it does not explicitly instruct any behavior, so we have excluded it from our analysis.

3.2 Extraction method for BF information

Methodology for Extracting BF Information

We utilize RoBERTa [14], a Transformer-based bidirectional language model for natural language understanding, to extract BF information from tweets on X. Our previous studies [15] have shown that RoBERTa provides a practical level of accuracy when compared to both rule-based approaches and other deep learning models. For our implementation, we use the PyTorch framework² and initialize the model with a Japanese pre-trained RoBERTa model³.

Preprocessing and Model Architecture

We first remove URLs and user account names from each tweet. We then use Juman++⁴ for morphological analysis. The resulting tokens are fed into the Japanese RoBERTa

²<https://pytorch.org/>

³<https://huggingface.co/nlp-waseda/roberta-base-japanese>

⁴<https://nlp.ist.i.kyoto-u.ac.jp/JUMAN>

model, and we extract the distributed representations from the final layer. These representations are then passed to a fully connected layer. We fine-tune the model so that the output of this layer classifies whether the input corresponds to BF information or not. We determined the following hyperparameters through a grid search: the number of hidden layers = 12, vector size = 768, batch size = 32, the number of epochs = 5, learning rate = 0.001, and dropout rate = 0.1. We adopt the Adam optimizer [16] for training.

Dataset and Evaluation

For fine-tuning, we use a dataset of tweets posted during Typhoon Faxai (Typhoon No. 15), which struck the Bōsō Peninsula in Chiba Prefecture in September 2019⁵. The dataset consists of 24,430 tweets collected between September 6th and 18th, 2019. This dataset is balanced, with 12,215 tweets labeled as BF information and 12,215 as non-BF information. In this study, one tweet is considered a single instance of BF information. As our prior work [15] already includes a detailed comparative analysis of various models (e.g., rule-based, Bi-LSTM, BERT, and RoBERTa), this paper shows only the results of a five-fold cross-validation for the RoBERTa model, as shown in Table 1. Table 1 demonstrates that the RoBERTa-based model achieves higher accuracy in extracting BF information. Therefore, we have adopted this model for our further analysis of disaster-related tweets.

Table 1: Performance of BF information extraction model

Model	Precision	Recall	F1-score	AUC
RoBERTa	0.900	0.949	0.924	0.973

4 Classification of BF information types

We propose a classification model that categorizes the extracted BF information into predefined BF information types, as described below.

4.1 Definition of BF information types

BF information includes various forms of information that encourage or discourage specific actions, such as “Please be careful with...” or “Do not...” Yamamoto et al. [17] extract BF information during large-scale disasters and conducted a feature analysis, based on which they proposed the following five types of BF information:

- **Suggest Type**
This type includes content that recommends the readers take a specific action. For instance: “The nearby river is rising. Please evacuate immediately.”
- **Inhibition Type**
This type discourages or prohibits the readers from

taking certain actions. For example: “The river is swelling due to heavy rain. Please avoid approaching it.”

- **Encouragement Type**

This type contains content aimed at emotionally encouraging the readers. For example: “There are still power outages and food shortages, but let’s keep going together.”

- **Wish Type**

This type expresses the poster’s own wishes. For example: “We don’t have enough food. Please come and help us soon.”

- **Other Type**

This type includes information that does not classify any of the above types.

4.2 The BF information type classification model

We utilize the Japanese pre-trained RoBERTa model as the base for our classification framework. Fine-tuning is performed using a dataset of disaster-related tweets, each annotated with one or more of the four BF information types. Feature vectors are obtained from the final output layer of RoBERTa, specifically from the representation corresponding to the [CLS] token.

Prior to inputting the tweets into the model, we conduct morphological analysis using Juman++⁶. As part of the preprocessing, URLs and user account names (handle names) are removed from the tweet texts.

The hyperparameters of the RoBERTa model are determined using grid search. The number of hidden layers is set to 12, the vector size to 768, batch size to 16, learning rate to 0.000005, and dropout rate to 0.1. We adopt AdamW as the optimizer for training.

(1) Independent (Single-Label) Models

We construct separate binary classifiers for each of the four BF information types. Each classifier independently determines whether its corresponding label should be assigned to a given piece of BF information. For each binary classifier, the input representation is taken from the final hidden state corresponding to the [CLS] token in the RoBERTa model. This vector is fed into a fully connected layer and fine-tuned to perform binary classification. By aggregating predictions across the four classifiers, we achieve multi-label classification.

(2) Unified Multi-Label Model

We also construct a single model that simultaneously performs multi-label classification across all four BF information types. In this approach, a four-dimensional fully connected layer is added to the

⁵<https://ja.wikipedia.org/wiki/>

⁶<https://nlp.ist.i.kyoto-u.ac.jp/JUMAN>

[CLS] token output of the final layer. A sigmoid activation function is applied to each unit, and the resulting values represent the probability that each corresponding label applies. Labels with predicted probabilities exceeding a threshold of 0.5 are assigned to the input instance. This model allows for simultaneous prediction of multiple labels in a single forward pass.

4.3 Evaluation of the BF information type classification model

To assess the effectiveness of the proposed classification model for BF information types, we conducted evaluation experiments.

4.3.1 Evaluation data

For the evaluation of our model, we used data from two major typhoons: (1) Typhoon Faxai in 2019 (September 6–18), and (2) Typhoon Nanmadol in 2022 (September 16–27). Typhoon Faxai was characterized by heavy rainfall, while Typhoon Nanmadol featured strong winds.

We use crowdsourcing to annotate the 10,000 extracted tweets of BF information with their respective information types. A total of ten annotators participated in this task. Each tweet could be assigned one or more of the following four labels: “suggest,” “inhibition,” “encouragement,” and “wish.” Annotators were allowed to assign one or more labels to a single instance if applicable. For each BF information, if six or more annotators agree on a particular label, that label is assigned to the tweet. BF information that does not satisfy this criterion is regarded as “Others” and is excluded from consideration in this study. BF information that does not meet the threshold of six is classified as “Others” and excluded from use in this study. The results of the multi-label annotation conducted via crowdsourcing are shown in Table 4. The counts for each BF information type include instances that may have been labeled with multiple types—for example, those labeled as both “Suggest” and “Inhibition” are counted in both categories. As seen in Table 4, there is an evident imbalance in the number of instances per label. The decision to annotate only 10,000 tweets was made to reduce the annotation cost; however, this led to a shortage of data for specific labels. To address this, we applied oversampling. Among the various oversampling techniques, we adopted Easy Data Augmentation (EDA) [18]. We set the EDA hyperparameter α to 0.05 and the number of generated samples per original tweet (n_{aug}) to 16. We used the implementation available in daaja⁷ to perform the augmentation. The number of instances before and after oversampling is presented in Table 3.

4.3.2 Validation of oversampling

To evaluate the effectiveness of the oversampling process, we compared model performance before and after applying EDA (as shown in Table 3). The same model architecture was used in both conditions.

For fine-tuning, we performed five-fold cross-validation using 80% of the data for training and 20% for testing. As shown in Table 6 (1) and (2), the models trained using oversampled data consistently performed better than the models trained using non-oversampled data. These results validate the utility of the oversampling method, and we therefore adopted the oversampled dataset for training in this study.

4.3.3 Evaluation of the classification model

To further validate the proposed BF information type classification model, we conducted a comparative experiment. Our proposed model performs multi-label classification. As a baseline, we constructed binary classification models—one for each label—where each model distinguishes between positive and negative examples of that label.

All models used the RoBERTa Japanese Pretrained model. For binary classification, 20% of the oversampled data for each label was used as positive examples, while the same number of negative examples (instances without that label) was randomly sampled. This resulted in a total of four binary classifiers. Both the proposed multi-label model and the binary classifiers were trained using five-fold cross-validation on the oversampled data shown in Table 5.

Table 6 shows the results. While the binary classifiers (3) achieved slightly better performance in terms of accuracy, precision, recall, F1-score, and AUC, the proposed model (1) required 3.93 times less computation time. This is because the binary classifiers needed to evaluate each instance using four separate models. Thus, considering both performance and efficiency, the proposed model demonstrates effectiveness in classifying BF information types.

5 Analysis of the relationship between personality traits and types of BF information

The relationship between the readers’ personality traits and the types of BF information is analyzed through the following procedure:

1. Determine the personality traits of potential participants using the TIPI-J questionnaire.
2. Select participants based on the results obtained in step (1).
3. Administer a questionnaire to the participants regarding the perceived usefulness of BF information.

⁷<https://github.com/kajyuen/daaja>

Table 2: Number of BF information per typhoon

No.	Typhoon	Total Instances	Instances Used for Training
1	Faxai (2019)	12,215	5,000
2	Nanmadol (2022)	67,378	5,000

Table 3: Number of BF information before and after oversampling

Type	Before oversampling	After oversampling
Suggest	985	16,745
Inhibition	260	4,420
Encouragement	491	8,347
Wish	798	13,566

Table 4: Labeling results of BF information types

Label	Number of BF information
Suggest	8,078
Inhibition	122
Encouragement	230
Wish	617
Suggest and Inhibition	132
Suggest and Encouragement	249
Suggest and Wish	163
Wish and Encouragement	10
Inhibition and Wish	6
Suggest, Wish, and Encouragement	2
Others	391

- Analyze the relationship between the readers' personality traits and the types of BF information based on the questionnaire results.

5.1 Questionnaire survey

5.1.1 Determination of personality traits

This study uses the Big Five personality traits, a widely accepted model in psychology, to determine the readers' personality. As shown in Table 7, the Big Five model categorizes human personality into five factors: "Extraversion," "Agreeableness," "Conscientiousness," "Neuroticism," and "Openness." To identify these traits, we conducted a questionnaire survey based on the Big Five model. To minimize the burden on participants, we used the Ten Item Personality Inventory – Japanese version (TIPI-J), proposed by Oshio et al. [19]. This scale measures personality traits using only ten questions, which are presented in Table 8. For each item, participants provided their responses on a seven-point Likert scale, ranging from "1: Strongly disagree" to "7: Strongly agree."

5.1.2 Selection of participants

The TIPI-J allows for flexible determination of individuals with high or low levels of each personality trait. In this study, the thresholds for each personality trait were determined based on a crowdsourcing based survey. The questionnaire in Table 8 was administered to 1,000 male and female participants aged 20 or over as a screening survey.

The results showed that, for all personality traits, a score of 8 was significantly more frequent than other scores. Therefore, in this study, we define individuals scoring 10 or higher (i.e., +2 points above the base score of 8) as having "high" levels of that trait, and individuals scoring 6 or lower (−2 points or more below 8) as having "low" levels of that trait. Furthermore, individuals often possess multiple personality traits. For the analysis of the relationship between personality traits and BF information types, it is necessary to decide whether to analyze each trait independently or to account for combinations of traits. In the former approach, a participant with both high extraversion and high openness is treated separately as "high extraversion" and "high openness." In the latter, the same participant would be treated as "high in both extraversion and openness," and not as "high extraversion" or "high openness" individually. To make this decision, we calculated the correlation coefficients between traits. If strong correlations were observed, an analysis considering multiple traits would be warranted. The correlation coefficients are shown in Table 10. We find that the highest correlation coefficient was 0.48, indicating only weak correlations between traits. Therefore, in this study, we analyze each trait independently without accounting for inter-trait influences. From the screening survey results, individuals with high and low scores for each trait were extracted, resulting in 248 participants. The distribution of participants by personality trait is shown in Table 11.

When selecting participants for each trait, three patterns can be considered:

- Select only individuals who have high (or low) levels of the target trait and do not have high (or low) levels in any other trait.
- Select individuals with high (or low) levels of the target trait regardless of other traits, but do not reuse their data for other traits.
- Select individuals with high (or low) levels of the target trait regardless of other traits, and allow reuse of their data for other traits.

Pattern (1) has the drawback of resulting in very few eligible participants. Pattern (2) may lead to variations in analysis results depending on which individuals are selected. Therefore, in this study, we adopt Pattern (3).

5.1.3 Survey data

The data used for the questionnaire survey was collected during Typhoon No. 15 in 2022 (September 22nd–24th, 2022). We used our proposed BF information extraction

Table 5: Number of positive and negative data

Type	Positive Samples	Negative Samples	Total
Suggest	985	985	1,970
Inhibition	260	260	520
Encouragement	491	491	982
Wish	798	798	1,596

Table 6: Performance results of each model

Model	Type	Accuracy	Precision	Recall	F1-score	AUC
(1) Proposed Model	Suggest	0.958	0.973	0.969	0.971	0.981
	Inhibition	0.992	0.930	0.952	0.940	0.996
	Encouragement	0.971	0.886	0.912	0.898	0.981
	Wish	0.984	0.968	0.956	0.962	0.994
	Average	0.976	0.939	0.947	0.943	0.988
(2) Multi-label Model (Without Oversampling)	Suggest	0.878	0.893	0.949	0.920	0.926
	Inhibition	0.961	0.512	0.515	0.512	0.930
	Encouragement	0.914	0.650	0.500	0.545	0.914
	Wish	0.927	0.889	0.762	0.819	0.963
	Average	0.920	0.736	0.682	0.699	0.933
(3) Single-Label Models	Suggest	0.966	0.961	0.972	0.966	0.992
	Inhibition	0.990	0.989	0.992	0.990	0.998
	Encouragement	0.969	0.961	0.978	0.969	0.993
	Wish	0.986	0.983	0.989	0.986	0.995
	Average	0.978	0.973	0.983	0.978	0.994

Table 7: Descriptions and characteristics of each big five trait

Trait	Description	Characteristics
Extraversion	Measures sociability, proactivity, and activeness	Individuals with high extraversion tend to take action immediately once they have an idea, and are energetic. They are assertive, capable of expressing their opinions, and skilled at speaking in front of large groups. They may feel bored in environments lacking stimulation.
Agreeableness	Measures empathy, consideration, and compassion toward others	Individuals with high agreeableness enjoy pleasing and serving others, and tend to prioritize others' success over their own. They dislike conflict and may suppress their own opinions to maintain harmony and facilitate smooth interactions.
Conscientiousness	Measures self-control over emotions and actions, and a strong sense of responsibility	Individuals with high conscientiousness are focused and disciplined toward clear goals, demonstrating perseverance and responsibility. They tend to think carefully before acting, which may slow down their behavior.
Neuroticism	Measures the intensity of responses to negative stimuli	Individuals with high neuroticism are more sensitive to negative events and prone to stress. They may become irritated or panic when things do not go as planned.
Openness	Measures intellectual curiosity and imagination	Individuals with high openness actively engage in new experiences and enjoy novel environments. They are skilled at expressing their feelings and emotions to others, and tend to dislike being constrained by strict rules.

and classification models to categorize the BF information by type. From the 51,599 BF information automatically extracted by our proposed model, the classification results were as follows: 22,911 of the **Suggestive** type, 588 of the **Inhibitive** type, 1,983 of the **Encouragement** type, and 2,959 of the **Expressive** type, with the remainder categorized as **Other**. We randomly sampled 50 instances from each of the four main types to create our experimental dataset.

5.1.4 Flow of survey

We used a crowdsourcing platform to conduct a questionnaire survey with the selected participants. The survey data, which were categorized by BF information types, were presented to the participants randomly. Participants were instructed beforehand to imagine themselves as victims of a major typhoon and to answer each question from that perspective. They were asked to read each tweet with BF information and respond to a corresponding question based on the type: “Did you want to take action?” for the Suggestive

Table 8: TIPI-J questionnaire items for personality trait assessment

Item	Question
1	I see myself as active and extraverted.
2	I see myself as someone who has complaints about others and tends to get into conflicts.
3	I see myself as dependable and self-disciplined.
4	I see myself as anxious and easily upset.
5	I see myself as open to new experiences and having unconventional ideas.
6	I see myself as reserved and quiet.
7	I see myself as considerate and kind to others.
8	I see myself as disorganized and careless.
9	I see myself as calm and emotionally stable.
10	I see myself as lacking in creativity and ordinary.

Table 9: Calculation method for personality traits

Trait	Calculation
Extraversion	Item 1 + (8 - Item 6)
Agreeableness	Item 7 + (8 - Item 2)
Conscientiousness	Item 3 + (8 - Item 8)
Neuroticism	Item 4 + (8 - Item 9)
Openness	Item 5 + (8 - Item 10)

type, “Did you want to stop the action?” for the Inhibitive type, “Did you feel encouraged?” for the Encouragement type, and “Did you want to respond to the request?” for the Expressive type. Responses were rated on a four-point Likert scale, with “1: Strongly disagree,” “2: Disagree,” “3: Agree,” and “4: Strongly agree.”

5.1.5 Survey results

In this study, we regard BF information with higher evaluation scores in the questionnaire results as more “effective information.” In this study, we define “effective information” as BF information presented to the reader that they perceive as prompting them to take the action described. Table 12 shows the average questionnaire results. The scores shown here are the raw evaluation scores from the questionnaire.

5.2 Analysis of relationship between personality traits and BF information types

Based on the survey results, we performed three types of analysis: a comparative analysis of high vs low personality trait groups, a comparison between different personality traits, and a comparison between different BF information types.

5.2.1 Comparative analysis by high and low levels of each personality trait

We conducted this analysis to understand the characteristics of how each personality trait influences the effectiveness of

different BF information types. We used the survey results from Table 12. As our analytical method, we employed the **Brunner-Munzel test**, which is suitable for comparing two independent groups without assuming equal variances. We conducted a one-sided test at a 5% significance level. The null hypothesis (H_0) was that “there is no difference in the perceived effectiveness between the high and low personality trait groups.” The alternative hypothesis (H_1) was that “the high personality trait group perceives the information as more effective than the low personality trait group.”

In this analysis, we focused on comparing the high and low groups for each specific trait and did not consider the interactions between different traits. Therefore, we did not apply multiple comparison corrections such as the Bonferroni correction. The results are shown in Table 13.

Results and Discussion

A significant difference ($p < 0.05$) was found for the **Encouragement** and **Expressive** types in the high Extraversion group compared to the low Extraversion group. This suggests that highly extraverted readers find these types of BF information more effective. We believe this is because extraverted individuals are more sociable and are thus more likely to respond to BF information of collective encouragement (“Let’s keep going”) or requests for help (“Please come and help us soon”).

For the high Agreeableness group, a significant difference ($p < 0.05$) was also found for the **Encouragement** and **Expressive** types. People with high Agreeableness tend to cooperate more with others. Therefore, they are more likely to respond to BF information like “Please...” or “Let’s work together.” No significant differences were found for any BF information type in either the high Conscientiousness or high Neuroticism groups. This indicates that the level of Conscientiousness or Neuroticism does not significantly affect the perceived effectiveness of any BF information type.

For the high Openness group, significant differences ($p < 0.05$) were found for the **Suggestive**, **Encouragement**, and **Expressive** types. This suggests that readers with high Openness find these types of BF information more effective than those with low Openness. We believe this is because people high in Openness are more accepting of new experiences and are generally more proactive, mak-

Table 10: Correlation coefficients for personality traits (1,000 participants)

	Extraversion	Agreeableness	Conscientiousness	Neuroticism	Openness
Extraversion	1	0.03	0.32	-0.40	0.42
Agreeableness	0.03	1	-0.41	-0.40	0.09
Conscientiousness	0.32	-0.41	1	-0.48	0.32
Neuroticism	-0.40	-0.40	-0.48	1	-0.30
Openness	0.42	0.09	0.32	-0.30	1

Table 11: Number of survey participants for each personality trait

Personality Trait	High	Low
Extraversion	73	111
Agreeableness	119	61
Conscientiousness	82	106
Neuroticism	94	84
Openness	58	112

ing them more likely to act on these types of information.

5.2.2 Analysis of the relationship between personality traits and BF information types

(a) Analysis Method by Personality Trait

We evaluate which information types are effective for each personality trait to analyze the relationship between personality traits and types of BF information. In this analysis, we use standard scores (deviation values) to capture both the variation within a single trait group and overall tendencies, enabling comparison across different personality traits.

The standard score $TP_{p,i}$ for personality trait p with respect to BF information type i is calculated using the following formula:

$$TP_{p,i} = \left(\frac{\alpha_{p,i} - \mu_p}{\sigma_p} \right) \times 10 + 50$$

Here, $\alpha_{p,i}$ is the score of personality trait p for information type i , μ_p is the mean score for personality trait p , and σ_p is the standard deviation of scores for personality trait p . In this analysis, we define information types with a standard score above 55 as “effective” for a given personality trait, and those below 45 as “ineffective.”

(b) Analysis Results and Discussion by Personality Trait

The results of this analysis are shown in Figure 1. The results indicate that for individuals with high levels of extraversion, agreeableness, or conscientiousness, similar patterns are observed: the inhibitory and encouraging types are effective, while the Suggest and Wish types are not.

For highly extraverted individuals, this may be because they tend to respond quickly and sensitively to stimuli. Therefore, inhibitory BF information such as “please refrain from...” likely elicited strong reactions. Additionally, since extraverted individuals are typically communicative, encouraging BF information like “please do your best” may

have resonated with their Wish for connection with others. Individuals with high agreeableness tend to compromise and tolerate discomfort. This may explain their receptiveness to inhibitory BF information. Furthermore, due to their prosocial tendencies—such as the Wish to please or help others—they may have also responded well to encouraging BF information. However, despite the assumption that wishful BF information (e.g., “Please...”) might also be effective for agreeable individuals, the results did not support this. Clarifying this discrepancy remains a topic for future work. Conscientious individuals are known for their tendency to deliberate carefully before acting. As such, they may be more inclined to follow inhibitory guidance. Their trait of being reliable and responsible might also explain the effectiveness of encouraging BF information.

For individuals with high neuroticism, inhibitory information types were found to be effective. This may be due to their heightened sensitivity to emotions and perceived threats in their environment. BF information like “Do not...” likely evoked a stronger sense of urgency or risk, which could have prompted behavioral restraint.

For individuals with high openness, encouraging BF information is effective. This could be attributed to their self-awareness and expressiveness. People who are high in openness are generally good at communicating their feelings, so BF information like “Do your best” may have appealed to their introspective and expressive nature.

5.2.3 Analysis of the relationship between BF information types and personality traits

(a) Analysis Method by BF Information Type

We analyze the relationship between each BF information type and personality traits. As with the previous analysis that examined personality traits by information type, we use standard scores (deviation values) to allow for comparison across traits and account for internal variation. The standard score $TB_{b,j}$ for BF information type b and personality trait j is calculated using the following formula:

$$TB_{b,j} = \left(\frac{\alpha_{b,j} - \mu_b}{\sigma_b} \right) \times 10 + 50$$

Here, $\alpha_{b,j}$ is the score of personality trait j for information type b , μ_b is the mean score across all traits for information type b , and σ_b is the standard deviation for information type b . In this analysis, we define personality traits with a

Table 12: Average scores for each BF information type by high and low personality traits

Trait	Group	Suggestive	Inhibitive	Encouragement	Expressive
Extraversion	High	2.141	2.461	2.492	2.314
	Low	1.952	2.363	2.207	2.043
Agreeableness	High	2.069	2.452	2.421	2.257
	Low	1.924	2.378	2.132	1.947
Conscientiousness	High	2.082	2.452	2.426	2.270
	Low	1.937	2.380	2.203	2.039
Neuroticism	High	2.041	2.452	2.295	2.153
	Low	2.136	2.448	2.410	2.254
Openness	High	2.222	2.442	2.543	2.350
	Low	1.856	2.352	2.166	1.997

Table 13: Statistical results for each personality trait

Trait	Statistic	Suggestive	Inhibitive	Encouragement	Expressive
Extraversion	Statistic	-1.243	-0.861	-2.259	-2.352
	<i>p</i> -value	0.108	0.195	0.013	0.010
Agreeableness	Statistic	-1.060	-0.681	-2.148	-2.739
	<i>p</i> -value	0.146	0.248	0.017	0.004
Conscientiousness	Statistic	-0.740	-0.524	-1.472	-1.575
	<i>p</i> -value	0.230	0.301	0.071	0.058
Neuroticism	Statistic	0.476	0.030	0.798	0.543
	<i>p</i> -value	0.682	0.512	0.787	0.706
Openness	Statistic	-2.159	-0.739	-2.645	-2.444
	<i>p</i> -value	0.017	0.231	0.005	0.008

standard score above 55 as being effectively influenced by the given information type, and those with a score below 45 as not effectively influenced.

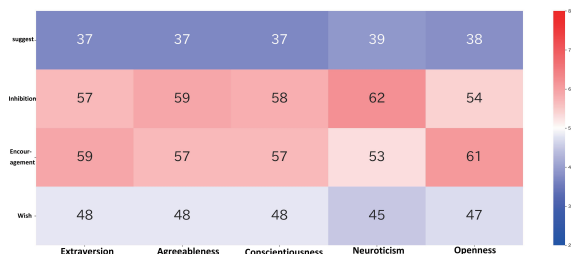


Figure 1: Results of BF information type by personality traits

(b) Analysis Results and Discussion by Information Type

The results are shown in Figure 2. For the Suggest type, individuals with high openness showed positive responsiveness, while those with high agreeableness and neuroticism were less responsive. The standard score was highest for individuals with high openness, likely because such individuals are characterized by flexible thinking and a willingness to act in novel situations, enabling them to adapt well to prompts like “Please do....” Conversely, individuals with high neuroticism had the lowest standard scores. This is likely due to their tendency to experience heightened anxiety in disasters, making it difficult for them to respond appropriately to behavior-prompting BF information. Al-

though agreeable individuals are typically kind and receptive to advice, the results did not show effectiveness for this group, contrary to expectations. Clarifying this discrepancy is a topic for future research.

For the inhibitory type, individuals with high extraversion responded positively, while those with high openness did not. Extraverted individuals tend to respond quickly to stimuli and are highly sensitive to urgency, which may explain why they were more responsive to BF information like “Please do not....” On the other hand, highly open individuals prefer change and action, making inhibitory BF information less effective for them.

For the encouragement type, both extraverted and open individuals showed positive responses, while those with high neuroticism did not. The highest standard score was observed among individuals high in openness. Their emotional sensitivity likely enabled them to resonate with BF information such as “You can do it,” even when received from unknown users on social media. In contrast, neurotic individuals, who are prone to pessimism, may not have felt encouraged by such BF information.

For the Wish type, individuals with high extraversion and openness were again responsive, while those with high neuroticism were not. This pattern is similar to that observed with the encouragement type. Extraverted people tend to communicate easily even with strangers, and open individuals are emotionally receptive and willing to act in unfamiliar environments. These traits likely contributed to their positive responses to requests such as “Please help” on social media.

In contrast, individuals with high neuroticism tend to experience heightened anxiety during disasters, which may have left them unable to respond to such appeals.

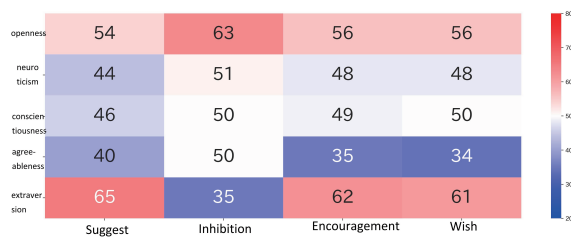


Figure 2: Results of Personality Traits by BF Information Type.

6 Conclusion

This study has proposed a method for extracting behavioral facilitation (BF) information from social media during disasters and classifying it into four categories: “Suggest,” “Inhibitory,” “Encouragement,” and “Wish.” We applied the method to typhoon-related SNS posts, conducted a crowdsourcing-based survey, and analyzed the relationship between BF information effectiveness and readers’ personality traits measured by the Big Five. Results showed that high extraversion and agreeableness were associated with greater receptiveness to Encouragement and Wish types, while high openness was linked to Suggest, Encouragement, and Wish types. No significant differences were found for conscientiousness and neuroticism.

Future work will examine BF information effective for low trait scores, investigate traits with no significant differences, extend the analysis to other disaster types, and address the impact of misinformation.

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