Modeling the Social Acceptability of Technologies Using Twitter Data

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***Abstract*—Our society is built on the benefits of technological development, but this development also entails risks. When the convenience of a new technology outweighs the sense of anxiety about its risks, we can consider that this technology is socially accepted. In this study, we use the social media to analyze the general public's anxiety feelings toward various technologies and model the social acceptability of the new technologies based on this analysis. In this study, 6,452,730 tweets about three technologies: "automated driving," "electronic currency," and "drones" were collected, and the social acceptability of the technologies was examined using emotion classification, text categorization, and topic analysis techniques. As a result, we concluded that the anxiety about unemployment can be one perspective for analyzing the social acceptability of a technology.**

Keywords—Twitter, emotion classification, social acceptability, text categorization, topic analysis

I. Introduction

Our society is built on the benefits of technological development, but there are always risks involved. For example, automated driving technology could make better use of time for people living in suburbs and commuting to cities, and could improve the lives of people living in depopulated areas without public transportation. On the other hand, everyone must have felt the uneasiness about the safety of automated driving technology. When the convenience of a new technology outweighs such concerns, the technology can be considered socially accepted. In this study, we use the social media to analyze the anxiety feelings of the general public toward various types of technology, and model the social acceptability of the technologies based on this analysis.

It is considered that the anxiety toward new technologies can transform over time. For example, if you search for automated driving on Twitter, tweets around 2010 are centered on vague concerns such as "I'm quite worried about automated driving buses," but by 2021, tweets are more specific such as "I'll be happy when automated driving cars become common, but I guess it will be a long time before automated driving is possible even on snowy roads." As in the latter tweet, the concern has become more concrete. The person who posted this tweet believes that automated driving technology can be used in everyday life to some extent unless under special situations such as snowy roads. It can be assumed that the type of anxiety changed between 2010 and 2021, and that somewhere in that time, automated driving technology became socially accepted.

In this research, we first collect the anxiety that people have about three technologies, which are "automated driving," "electronic currency," and "drones," from Twitter using emotion classification. Next, we will use text categorization and topic analysis techniques to clarify when these technologies can be said to have become socially accepted.

The contributions of this paper are as follows.

- Modeling social acceptability of technologies by analyzing a total of 6,452,730 tweets,
- Highly reproducible analysis of tweets using state-of-the-art natural language processing techniques,

- Proposal of training data construction method for automatically categorizing tweets in a very short time (2,465 tagged-tweets in one day).

II. Related Works

Fukuda et al. [1] classified the tweets about the coronavirus vaccine by emotion, and found out how the percentage of tweets with each emotion changed in Japan, the United States, the United Kingdom, Canada, Australia, and India. We also analyze the temporal trend of tweets, but differ in that we model the social acceptability of the technologies based on the analysis results.

Dahal et al. [2] analyzed a large-scale dataset of geotagged tweets containing specific keywords related to climate change using text mining techniques such as volume analysis, sentiment analysis, and topic modeling. The content of the debate and the differences between countries were clarified. They used Latent Dirichlet Allocation (LDA) [3] as a topic modeling method, but LDA ignores the semantic relationships between words and has the problem of not being able to interpret the meaning of words in consideration of the context.

To address this problem, text embedding methods represented by BERT [4] have been rapidly spreading in recent years. Grootendorst [5] showed that a new topic modeling method, BERTopic, which utilizes embedded representations of text and class-based TF-IDF, can classify with high accuracy. Thus, we use BERTopic for topic analysis. However, since BERTopic uses HDBSCAN for text clustering, there may be a problem that outliers (when only one document belongs to one cluster) increase. Therefore, we use the k-means method instead of HDBSCAN as the text clustering method.

III. Modeling the Social Acceptability of Technologies

In order to determine the social acceptability of new technologies, it is necessary to understand the public's concerns and to identify how these concerns have changed over time. In this study, we model the social acceptability of a technology through the following three steps.

(A) Collection of anxiety tweets

(B) Classification of anxiety tweets

(C) Modeling of social acceptability of technology by topic analysis of anxiety tweets

The details of each procedure are described below.

A. Collection of Anxiety Tweets

We use the Twitter API to collect tweets written in Japanese about “automated driving,” “electronic currency,” and “drones.” The search queries used for collection are shown below.

- **自動運転 (automated driving):** 自動運転 (automated driving) OR ドライバーレスカー (driverless car) OR セルフドライビングカー (self-driving car) OR 無人運転 (driverless)
- **電子マネー (electronic currency):** 電子マネー (electronic currency) OR キャッシュレス決済 (cashless payment) OR おサイフケータイ (mobile wallet) OR スマホ決済 (smartphone payment) OR スマートフォン決済 (smartphone payment) OR QR決済 (QR payment) OR コード決済 (code payment) OR バーコード決済 (barcode payment) OR 非接触型決済 (contactless payment) OR タッチ決済 (touch payment) OR モバイルウォレット (mobile wallet) OR デジタルウォレット (digital wallet) OR 交通系IC (transportation IC)
- **ドローン (drone):** ドローン (drone)

Next, we classify the collected tweets by emotion to extract anxiety tweets using BERT [1] [4] and T5 [2] [6] to construct the emotion classifier. In this study, the model of BERT used is a Japanese pre-trained model from Inui and Suzuki Laboratory of Tohoku University, which was fine-tuned with 1,593,552 tweets collected from Twitter.

We also use a model for T5 that has been pre-trained on a Japanese corpus of approximately 100 GB. We construct two types of emotion classifiers: one that learns each emotion type independently, and one that learns all emotions at once.

The training data used to construct the emotion classifiers is WRIME [7], a tagged corpus for constructing emotion classifiers using machine learning. In this corpus, eight types of emotions, “joy,” “sadness,” “expectation,” “surprise,” “anger,” “fear,” “disgust,” and “trust,” were assigned to 40,000 tweets written in Japanese with an emotion intensity value of 0-3.

After constructing the two emotion classifiers, we compare the accuracy of both classifiers Next, we use the model with higher accuracy to extract tweets containing anxiety. We selected “fear” and “disgust” as the emotion types related to anxiety among 8 emotions, extracting only 3 out of 0-3 for the emotion intensity as tweets containing anxiety.

B. Classification of Anxiety Tweets

The emotion classifier constructed in the previous section is used to classify anxiety tweets. A report on key issues related to safety and security science and technology was written by the Committee on Safety and Security Science and Technology [8]. In this report, the factors that threaten safety and security are organized into three tiers. The first tier consists of 11 categories: “crime,” “accidents,” “natural disasters,” “war,” “cyberspace issues,” “health issues,” “food issues,” “social life issues,” “economic issues,” “political and administrative issues,” and “environmental and energy issues.” We use the 9 categories, excluding “health issues” and “food issues,” which are less relevant for our analysis, and the tweets that do not belong to these 9 categories are classified as “others,” for a total of 10 categories.

[1] https://github.com/cl-tohoku/bert-japanese

[2] https://github.com/sonoisa/t5-japanese

Generally, constructing a text classifier by machine learning requires a large amount of manually categorized text. However, preparing such data is time-consuming. Therefore, we create a manually-tagged corpus for machine learning in a very short time. The procedure consists of two steps. In step 1, we manually select 27 tweets, 3 per category, from the set of tweets collected in the previous section. In step 2, we use these 27 tweets as the training data and apply few-shot learning to automatically categorize a total of 2,465 tweets. We manually check these 2,465 tweets and correct if the automatically assigned category is wrong. Using these results, we build a classifier that classifies tweets into 9 categories. ChatGPT[3] (GPT-3.5) and T5 are used in steps 1 and 2, respectively.

Using this classifier, we categorize all tweets collected in the previous section. The tweets that are not categorized in any of the 9 categories are assigned the "other" category. It is theoretically possible to categorize all the tweets using the few-shot learning in step 1, but the problem is that the ChatGPT API is a paid service and it is very costly to categorize all the large number of tweets.

C. *Modeling of Social Acceptability of Technology by Topic Analysis of Anxiety Tweets*

After classifying all tweets into ten categories using the method in the previous section, the tweets in each category are analyzed using BERTopic [5]. This tool visualizes the number of tweets per cluster over time. Using this tool, we find the clusters that are related to the social acceptability of the technology. The details of the analysis are described in section V.

IV. EXPERIMENT

We conducted experiments to confirm the effectiveness of the emotion classification method proposed in Section III-A and the category classification method proposed in Section III-B.

A. *Emotion Classification of Tweets*

Experimental Data

To construct the emotion classifier, we use WRIME, a dataset for estimating emotion intensity in Japanese. In this experiment, we use 30,000 training data, 2,500 validation data, and 2,500 evaluation data without duplication, following the division of Kajiwara et al. [7].

Alternative Methods

Experiments were conducted using the following three methods.

- BERT
- T5 (learning all emotion types at once)
- T5 (learning each emotion type independently)

Evaluation Measures

The Quadratic Weighted Kappa (QWK) [20] was used to evaluate the emotion classifiers.

Experimental Results

Table I shows the experimental results. The highest accuracy for each emotion is shown in bold. The T5 model, which was trained for each emotion, obtained the highest accuracy for five of the eight emotions, and the highest values were also obtained for "fear" and "disgust," which were selected as the types related to anxiety in this study. The highest values were also obtained for "fear" and "disgust," which were selected as types related to anxiety. Therefore, the T5 model trained for each emotion is used to extract anxiety tweets.

TABLE I. EXPERIMENTAL RESULT OF EMOTION CLASSIFICATION

Emotion	BERT	T5 (learning all emotion types at once)	T5 (learning each emotion type independently)
Joy	0.6871	**0.7185**	0.7142
Sadness	0.5931	0.5916	**0.6180**
Anticipation	0.6650	0.6621	**0.6882**
Surprise	0.5732	0.5702	**0.5906**
Anger	**0.3794**	0.2977	0.2934
Fear	0.5480	0.5532	**0.5869**
Disgust	0.4704	0.4729	**0.5662**
Trust	0.2337	**0.3032**	0.3031
Average	0.5175	0.5212	**0.5451**

Discussion

The results of learning by BERT and evaluation by QWK in the experiment by Kajiwara et al. [7] were 0.386 for fear and 0.348 for disgust. Compared to these results, the BERT model used in our experiment showed a significant improvement in evaluation. This may be due to the fact that fine-tuning using tweet data allowed us to specialize in short sentences, which is a characteristic of data on social media.

B. *Anxiety Tweet Classification*

Experimental Data

The classifier was constructed using ChatGPT and a manually created anxiety tweet dataset; 1,725 out of 2,465 were used as training data, 370 as validation data, and 370 as evaluation data. Table II is a breakdown of the 2,465 tweets by category.

[3] https://openai.com/blog/chatgpt

TABLE II. EXPERIMENTAL RESULT OF TWEET CLASSIFICATION BY ANXIETY CATEGORY

Anxiety Category	Number of tweets	Anxiety Category	Number of tweets
Crime	201	Social life issues	397
Accidents	334	Economic issues	81
Natural disasters	27	Political and administrative issues	217
War	73	Environmental and energy issues	55
Cyberspace issues	75	Other	1,005

Evaluation Measures

Precision and recall were used to evaluate the anxiety tweet classifier.

Experimental Results

Table III shows the experimental results, which are good considering the fact that the classification is a multi-class classification of 10 categories, with an average precision and recall of more than 0.53.

TABLE III. EXPERIMENTAL RESULT OF TWEET CLASSIFICATION BY ANXIETY CATEGORY

Anxiety Category	Precision	Recall
Crime	0.48	0.64
Accidents	0.61	0.75
Natural disasters	0.33	0.50
War	0.60	0.40
Cyberspace issues	0.38	0.33
Social life issues	0.48	0.57
Economic issues	0.67	0.57
Political and administrative issues	0.68	0.72
Environmental and energy issues	0.40	0.20
Other	0.68	0.59
Average	0.53	0.53

Discussion

Regarding the evaluation results of the T5 classifier, although it was generally able to classify with high precision, for some categories, both precision and recall were below 0.3. In order to further improve precision, multi-label classification is considered necessary. The proposed method uses single-label classification, with one category assigned to each tweet, but in many cases, one label is not sufficient. The following is an example of a case where multiple labels are necessary.

- It occurred to me that AI can run over and kill people in order to protect passengers in automated driving. Who would be responsible in such a case? Do we have to agree in advance that all the responsibility goes to the passenger? It can do whatever it wants! It's too scary!

This tweet should be categorized as either "accidents" or "political and administrative issues," but in the results of this evaluation, it is categorized as "Other." The precision and recall could be improved by multi-labeling these problems.

V. ANALYSIS OF ANXIETY TWEETS ABOUT THE THREE TECHNOLOGIES AND THEIR SOCIAL ACCEPTABILITY

This section presents the results of extraction, classification, and topic analysis of anxiety tweets for the three technologies of automated driving, electronic currency, and drones.

A. *Data Used for Analysis*

Table IV shows the collection period for each technology, the total number of tweets, and the number of extracted anxiety tweets. Before the analysis, we excluded tweets containing URLs for all technologies, and tweets containing "applications" and "campaigns" for electronic currency.

TABLE IV. DATA USED FOR ANALYSIS

Technologies	Collected period	Number of tweets	Number of anxiety tweets
Automated driving	2006.3-2022.5	2,086,612	79,827
Electronic currency	2006.3-2022.5	1,619,275	81,239
Drones	2015.6-2022.12	2,746,843	112,393

B. *Temporal Trends in the Probability of Occurrence of Anxiety Categories*

Automated driving

For each technology we calculated the probability of occurrence by dividing the number of tweets in each anxiety category by the number of anxiety tweets on a yearly basis. Fig. 1 shows the trends in the probability of occurrence of automated driving by category.

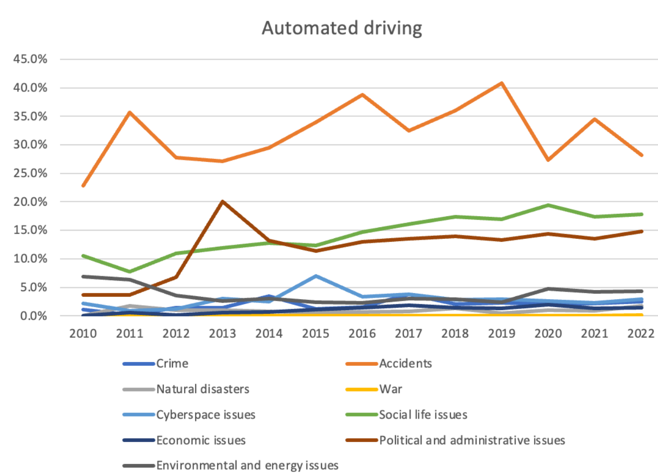

Fig. 1. Temporal trend in the probability of occurrence of anxiety categories (automated driving)

As can be seen from Fig. 1, the percentage of anxiety about "accidents" is always high, and that anxiety will account for more than 25% even in 2022. It can be inferred that anxiety has not been dispelled even with the spread of automated driving cars. Regarding "political and administrative issues," there were many opinions about who would be responsible for the accident and what kind of system the licensing would be, tweeted many times since 2013. Many tweets about driver unemployment are categorized as "social life issues," and the percentage is even higher now that Level 3 automated driving is seen across the city.

Electronic currency

Fig. 2 shows the trends in the probability of occurrence of electronic currency by category.

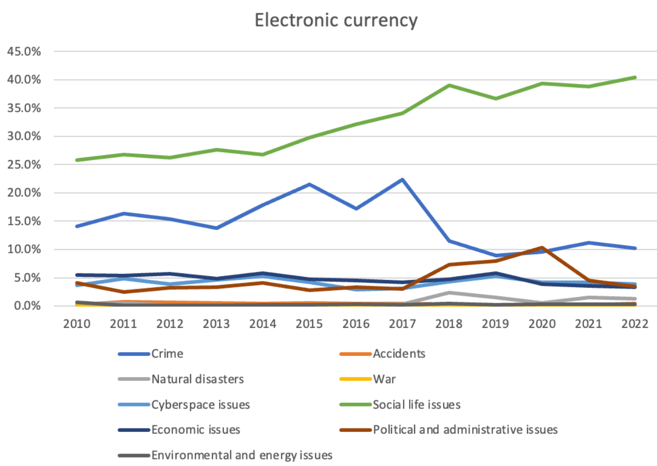

Fig. 2. Temporal trend in the probability of occurrence of anxiety categories (electronic currency)

From Fig. 2, the probability in "social life issues" is quite high and is increasing gradually. The next most common result was classified as "crime." Concerns about personal information and privacy were still present today. A similar opinion was also seen on "cyberspace issues." "Political and administrative issues" tended to increase around 2020. Looking at the tweets during the period, there were many voices calling for an extension and concerns about the economy in response to the end of the government's cashless payment point return business in the recession.

Drones

Fig. 3 shows the trends in the probability of occurrence of drones by category.

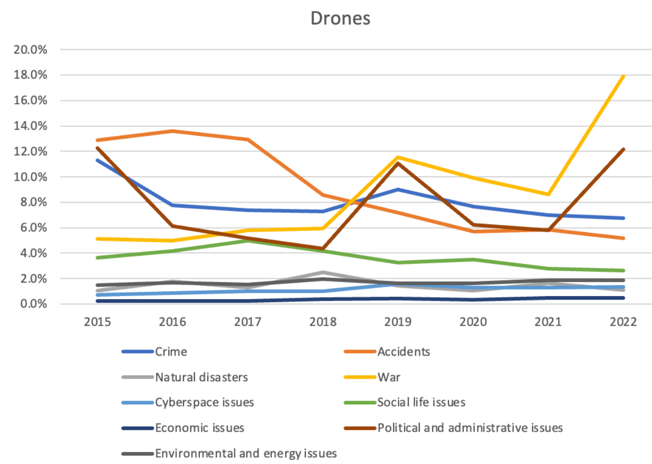

Fig. 3. Temporal trend in the probability of occurrence of anxiety categories (drone)

The ratio of each category has changed greatly depending on the period, and in recent years, anxiety about "war" has taken up a fairly large proportion. Looking at the tweets, the use of drones in the Ukraine war was a big topic, and there were many mixed opinions about the impact of technological progress on the war.

Since 2018, there has been an increase in political and administrative issues, such as opinions on flight area and weight regulations. The topic of "accidents" has been declining since 2016. One of the factors is the decrease in "accidents" due to stricter regulations. On the other hand, there were many doubts, anxieties, and harsh opinions about how to use the technology, contrary to the progress of the technology. As for "cyberspace issues," there were many voices of anxiety and worries about hacking and cyberattacks of drones, which appeared for automated driving as well.

C. *Social Acceptability of Technology*

Topic analysis using BERTopic clarified the chronological changes in anxiety factors within each category. Some of the topic analysis results for each technology are shown below.

Automated driving

Fig. 4 shows the results of the temporal trend analysis of unemployment in the "social life issues" category.

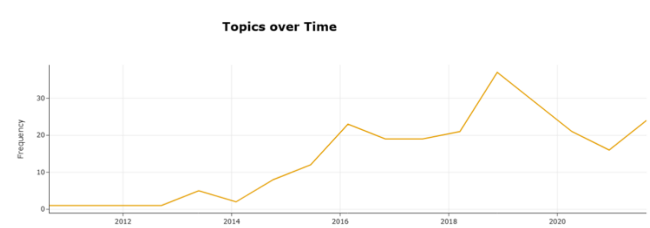

Fig. 4. Temporal trend of topic: Unemployment (automated driving)

As the topic of automated driving cars becomes more popular, we can see that the following unemployment-related topics are increasing. All these tweets were written in Japanese, but we translated them into English.

- When automated driving cars become fully practical, what will happen to the employment of taxis and bus drivers? I'm worried about other people.
- It would be nice to build a normal automated driving private car first, so why build a taxi that can carry passengers first? Do you really want to increase the number of unemployed by stealing drivers' jobs?
- First, you will lose your driver's license. It will be fully automatic. In other words, the job of a driver will disappear. This is the future one inch ahead. Companies that do not anticipate this at this stage will go bankrupt. surely.

Many automakers are setting out to develop automated driving cars, which has increased since 2015, and several US states have allowed automated driving cars to be tested on public roads. In 2016, the SAE (Society of Automotive Engineers) defined automated driving levels as six categories, and there were major movements related to automated driving during this period. The number of tweets about unemployment has started to increase around this time. In this way, concerns about unemployment against a new technology seem to indicate that the technology is being socially accepted.

Electronic currency

Regarding electronic currency, there were not many tweets about unemployment seen in automated driving, but there were opinions that worried about unemployment, such as the following.

- If convenience stores are unmanned and cashless payments are made, there is no need to restrain employees even if they are open 24 hours a day.
- If all payments are cashless, the working hours of a store cashier will be reduced by about 4 hours per day.

Drones

Fig. 5 shows the results of the temporal trend analysis of unemployment in the “social life issues” category.

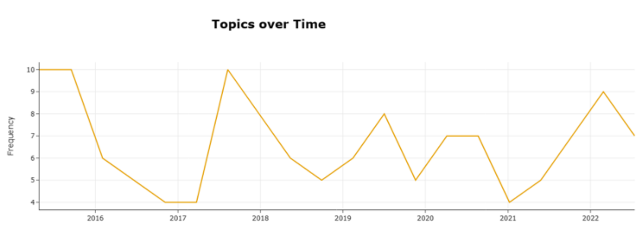

Fig. 5. Temporal Trend of topic: Unemployment (drones)

In this cluster, we saw the following tweets about whether drones would make people unemployed.

- At noon, lunch delivery men run around the Shanghai office on electric motorcycles, but in the next five to ten years, this landscape will be wiped out by unmanned delivery vehicles or drones. ....
- Combined with automated driving, it seems that home delivery will become unmanned. It seems to be faster than a drone. But if I open the door and these guys are there, I would be scared.
- There are unmanned convenience stores in China, and drone delivery experiments are being conducted in the United States. There is also a trend toward unmanned operations in Japan. It's really dangerous if you don't build up your strength before it's unmanned. I am getting stronger every day.

From the above analysis, we believe that the anxiety about unemployment can be one perspective for analyzing the social acceptability of technologies, although some tweets could not be collected enough to draw a graph of the transition depending on the technology.

VI. Conclusions

In this research, we examined the social acceptability of technologies using emotion classification, text classification, and topic analysis techniques, targeting 6,452,730 tweets about three technologies: automated driving, electronic currency, and drones. As a result, we concluded that anxiety about unemployment can be one of the perspectives for analyzing the social acceptability of technologies.

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