The Effect of Exposure to (Non-)like-minded Information on the Use of Political Incivility on Twitter *

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Abstract

Does exposure to like- and non-like-minded information lead to political incivility? Few previous studies have investigated this question, and the results have been mixed. There are two conflicting possibilities: (i) if individuals are frequently exposed to like-minded political information, their preexisting beliefs are reinforced and they are more likely to use uncivil language, and (ii) if individuals are frequently exposed to non-like-minded information, they often feel negative emotions and therefore are more likely to be uncivil. To evaluate these two competing hypotheses, the present study analyzes data from Japanese Twitter using a semi-supervised machine learning method. The results show that individuals who are exposed to non-like-minded information are more prone to political incivility.

Introduction

What makes people uncivil in online political discussions? While the proliferation of social media has made it easier for people to express their political opinions, it has also been observed that people tend to express their opinions in an uncivil manner or attack their political opponents online. In fact, more than one in five comments in online discussions are uncivil, according to Coe et al. (2014). Uncivil communication hinders consensus building. Hwang et al. (2018) demonstrated that uncivil discussion leads to negative emotions toward the other

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side and more expressions of disagreement. Popan et al. (2019) has also shown that when discussions are uncivil, individuals perceive lower levels of out-group rationality. Furthermore, several studies have revealed that uncivil political communication has direct and indirect negative effects on citizens' political trust and participation (Mutz and Reeves, 2005; Otto et al., 2020; Yamamoto et al., 2020).

Over the last two decades, a number of political communication researchers have focused on the ways in which people are exposed to political information online. Sunstein (2001) argued that on the Internet, individuals can easily form communities with other like-minded persons and are exposed to a large number of like-minded arguments offered by community members, thus, reinforcing their pre-existing opinions. Findings from empirical studies support Sunstein's argument (Stroud, 2010; J. Lee and Choi, 2020). On the other hand, some evidence has shown that exposure to contrary information leads to extreme opinions. When individuals are exposed to a balanced set of like-minded and non-like-minded arguments, this reinforces their preexisting attitudes because they tend to process contrary information skeptically (Taber & Lodge, 2006). This tendency has also been observed on Twitter. An experimental study has shown that conservative participants who were randomly assigned to follow a liberal Twitter bot became more conservative (Bail et al., 2018).

Despite this growing concern about the relationship between exposure to both like- and non-like minded information online and political attitudes, few studies have examined the relationship between exposure to both types of information and the use of incivility. F. L. Lee et al. (2019) have found that an increase in the level of cyberbalkanization (the state in which contents are frequently shared within communities, but not across communities) leads to a larger degree of political incivility on Facebook. This means that when individuals are frequently exposed to like-minded information, they are more likely to use uncivil language. This is because discussions with other like-minded persons intensify an individual's preexisting beliefs, which in turn leads to more extreme expressions (F. L. Lee et al., 2019). Although Lee and colleagues' work has made a significant contribution to this area of research, there is one problem: the unit of analysis was not the individual. This may lead to ecological fallacy problems. In other words, even though the degree of cyberbalkanization is correlated with the level of incivility at the collective level, this is not necessarily true at the individual level.

On the contrary, some studies have argued that exposure to non-like-minded information leads to the use of incivility. Hopp and Vargo (2019) have shown that individuals with high levels of bonded social capital are less likely to use political incivility on Facebook. The mechanism for this is that individuals with high levels of bonded social capital are more likely to connect with other like-minded persons, and therefore, do not frequently experience conflicts of opinions (Hopp & Vargo, 2019). Another study found that low levels of partisan polarity (i.e., high levels of partisan conflict) or high levels of racial heterogeneity in districts are positively correlated with the use of incivility on Twitter (Vargo & Hopp, 2017).

Although these studies are thought-provoking, they have three problems. First, previous studies have suggested two conflicting mechanisms. Second, the analysis at the individual level was insufficient. Third, few studies have directly focused on the ways in which individuals are exposed to political information on the Internet, where they have the freedom to choose their information sources from a wide range of options. To overcome these issues and provide new findings, the present study collects data from Japanese Twitter, and conducts individual-level analysis using a semi-supervised machine learning method. The results show that individuals who are exposed to non-like-minded information are more prone to political incivility.

Theory and Hypotheses

Exposure to like-minded information is thought to lead to incivility. As mentioned earlier, individuals reinforce their original opinions through selective exposure to like-minded information (J. Lee and Choi, 2020; Stroud, 2010; Sunstein, 2001). The more extreme an individual's views become, the greater the distance between their views and those of the out-group; thus, the more likely they are to perceive the out-group as a threat. To protect the in-group from the threat, they attack the out-group (Böhm et al., 2016). An empirical study has shown that individuals with extreme opinions are more likely to use uncivil expressions (Suhay et al., 2015), which supports the above mechanism. Thus, it is expected that individuals are more likely to post uncivil comments when exposed to like-minded information.

> H1: Internet users are more prone to political incivility when they are exposed to like-minded information.

On the contrary, exposure to non-like-minded information is also thought to lead to incivility. The key point here is that individuals who are exposed to non-like-minded information have more opportunities to experience conflicts with out-groups. Similar to the study mentioned earlier, individuals are likely to attack those from the out-group to protect the in-group (Böhm et al., 2016). Based on this finding, the more opportunities people have to be exposed to non-like-minded information posted by out-group members, the more frequently they perceive out-group threats; thus, the more likely they are to post uncivil comments.

> H2: Internet users are more prone to political incivility when they are exposed to non-like-minded information.

These two conflicting hypotheses are both theoretically plausible. Therefore, the present study adopts both of them as hypotheses and aims to clarify if either or neither one is correct through an empirical analysis.

Methods

To test these hypotheses, the present study conducted an analysis of data from Japanese Twitter using a semi-supervised machine learning method. As mentioned earlier, while the previous studies lacked individual-level analyses and direct indices for the degree of like-mindedness of information to which the individuals were exposed on Twitter, the methods of the present study overcome these problems.

Data

The present study collected Japanese tweets containing the name of a political party or its leader, and 500 tweets were extracted per day over eight weeks (for a total of 28,000 tweets). In addition, for each tweet, the list of people that the user who posted the tweet followed, the user's Twitter bio text, the Twitter bio texts of the people the user follows, and old tweets posted by the user within the first 30 days of opening their account were collected.

Dependent Variable

The level of incivility of the tweet served as the dependent variable. To index this variable, the present study used Latent Semantic Scaling (LSS) (Watanabe, 2020a), a semi-supervised machine learning method. The LSS evaluates the polarity of a text using the cosine similarity between the vector of seed words that represent each polarity and the vector of words in the text. According to Watanabe, the LSS can evaluate a text on the desired dimension if the appropriate seed words are selected for the purpose. Thus, by selecting typical uncivil and civil words as seed words, the present study applied the LSS to evaluate the level of incivility of tweets.

A word vector represents the meaning of a word in 200 dimensions. This vector is calculated using a technique called word embedding. While there are several methods for word embedding, the present study used Word2Vec (Mikolov et al., 2013). A pre-trained Word2Vec model, hottoSNS-w2v, was utilized because it was trained using a large scale Japanese corpus built from the text of blogs, Twitter, Japanese Wikipedia, and other web pages (Matsuno et al., 2019), making it suitable for the purpose of the study.

Text preprocessing was conducted as the first step to index the level of incivility. A tweet text was split into words using Mecab (Kudo, 2006) with mecabipadic-NEologd (Sato, 2015). Words without substantive meaning were excluded, such as numbers, URLs, and words included in SlothLib (SlothLib, n.d.) and Marimo (Watanabe, 2020b), or famous Japanese stop word lists. Function words (parts of speech other than nouns, verbs, adjectives, and adjectival verbs) were also excluded. Additionally, the names of political parties and party leaders were excluded, as these words are not necessary for assessing the level of incivility.

Seven uncivil and seven civil words were prepared (see Table 1), and the level of incivility was calculated according to the procedure proposed by Watanabe (2020a). The level of the incivility of a word was obtained by summing the cosine similarity of the vector of the word and the seven uncivil seed words, summing the cosine similarity of the vector of the word and the seven civil seed words multiplied by -1, and dividing the sum by 14 (see formula 1). The level of incivility of a tweet was obtained by calculating the level for all the words in the tweet using the above method and dividing the sum by the number of words (see formula 2, where *n* denotes the number of words).

$$\begin{aligned}\text{Incivility of a word} = \frac{1}{14}\{&\sum_{i=1}^{7}\text{cosine similarity}(\text{Uncivil seed word}_i, \text{Word}) \\ &+\sum_{i=1}^{7}\text{cosine similarity}(\text{Civil seed word}_i, \text{Word}) \times (-1)\}\end{aligned} \tag{1}$$

$$\text{Incivility of a tweet} = \frac{1}{n}\sum_{i=1}^{n}\text{Incivility of word}_i \tag{2}$$

Table 1: Seed Words

Polarity	Seed Words
Uncivil	バカ, アホ, 無能, 死ね, キモい, 糞, 売国奴
Civil	聡明, 優秀, 有能, 応援, ありがとう, 素敵, 誠実

Independent Variable (Mesurement 1)

The independent variable is the degree of like-mindedness of the information to which those who posted the tweets (hereinafter referred to as target users) were exposed on Twitter. The present study measured this by focusing on who the target users follow on Twitter. When people use Twitter, their Twitter home timelines show the tweets posted by other users that they follow (hereinafter referred to as followees). Thus, if they follow only others with the same political views as themselves, their home timelines show only tweets that express the same political views. On the contrary, if they follow others with diverse political opinions, their home timelines show a variety of political opinions. Therefore, by focusing on the degree of similarity in political views between target users and their followees, the level of like-mindedness of the information that they were exposed to on Twitter can be measured. Based on the above considerations, the present study used semantic similarity between target users' and their followees' Twitter bios as a measure of like-mindedness.

Word vectors representing the meaning of words were obtained using Word2Vec, while the meaning of the text was derived from averaging the vectors of words in the text. Furthermore, semantic similarity was obtained by calculating the cosine similarity of the two vectors representing the two texts. The present study utilized the hottoSNS-w2v, which was a pre-trained model of Word2Vec.

The specific procedure is described below. First, text preprocessing was conducted. The word vectors in the target user's bio were then averaged to get the vector of the bio. The same was done for the each of the followees' bios in order to obtain the vectors of their bios. Then the cosine similarity between the vector of the target user's bio and the vector of their followees' bios were calculated, summed up, and divided by the number of followees (see formula 3, where *n* denotes the number of followees). However, all target users and their followees who did not write their Twitter bios were excluded from the dataset.

$$\text{Like-mindedness} = \frac{1}{n}\sum_{i=1}^{n} \text{cosine similarity}(\text{Target user's bio}, \text{Followee's bio}_i) \tag{3}$$

Independent Variable (Mesurement 2)

To increase robustness, another measure of like-mindedness was created. This measure focused on members of parliament (MPs) among the followees and was calculated using the following formula:

$$\text{Like-mindedness} = \begin{cases} \dfrac{\text{Conservative MPs}}{\text{MPs}} & (\text{Conservative MPs} \geq \text{Liberal MPs}) \\[2ex] \dfrac{\text{Liberal MPs}}{\text{MPs}} & (\text{Conservative MPs} < \text{Liberal MPs}) \end{cases} \tag{4}$$

where MPs, conservative MPs, and liberal MPs refer to the number of MPs, conservative MPs, and liberal MPs followed by the target user, respectively.

It was assumed that most people follow more MPs who have the same political views as them than MPs who do not. If a target user followed only MPs who shared the same political views as them, the indicator was close to 1. In contrast, when they followed around an equal number of MPs on both sides, the indicator was close to 0.5. The criteria for labeling MPs as conservative or liberal are listed in Table 2.

Users who did not follow any MPs were excluded from the dataset since it would be impossible to calculate their indices. Those who followed only one legislator were also excluded from the dataset since it was highly likely that they only followed the MP since they were famous.

Table 2: The criteria for labeling MPs as conservative or liberal

Label	Criteria
Conservative	MP who belongs to the Liberal Democratic Party (自民党), Komeito (公明党), or Japan Innovation Party (日本維新の会)
Liberal	MP who belongs to Constitutional Democratic Party (立憲民主党), Japanese Communist Party (日本共産党), Social Democratic Party (社会民主党), or Reiwa Shinsengumi (れいわ新選組)
Excluded	MP who belongs to Democratic Party For the People (国民民主党) or The Party to Protect Citizens from NHK (NHK から国民を守る党)

Note: It is difficult to classify the Democratic Party For the People as either left or right, since its platform states that it aims to be "a citizens-driven, reforming centrist party that encompasses both moderate conservatives and liberals." In addition, it is difficult to place the Party to Protect Citizens from NHK on the left-right scale because it is a single-issue party and its issue is not ideological.

Control Variables

To address the possibility of reverse causality, where an originally aggressive person follows a non-like-minded person in the aim of attacking those who have opposing political views, the target user's initial level of incivility when they first opened their Twitter account was controlled for. As such, the initial incivility level was measured as the level of incivility of tweets posted during the first 30 days of opening the Twitter account. Additionally, the study controlled for the target users' duration of Twitter use, the number of people they followed, and the number of MPs they followed.

Regression Analyses

Multiple regression analyses were conducted using the data and variables described above. In addition to the analyses using a normal dataset, regression analyses were also conducted including only those users whose initial levels of incivility were below average (initially civil dataset). This is because the primary interest was to discover whether originally civil people could become uncivil through exposure to like-minded or non-like-minded information on Twitter.

Furthermore, prior to the analysis, if there were multiple tweets posted by the same user in the dataset, the values were averaged and aggregated into one row. This was done to avoid such users' data being overly reflected in the estimates.

Results

The results of the regression analysis using the normal dataset and measurement 1 are presented in Figure 1. These results show that *like-mindedness (1)* is statistically significantly associated with the *level of incivility* at the 5% level. That is, the more non-like-minded information individuals are exposed to on Twitter, the more uncivil their tweets are. This finding rejects Hypothesis 1 and supports Hypothesis 2. Similarly, as shown in Figure 2, the results of the analyses using the initially civil dataset and measurement 1 show that *like-mindedness (1)* was correlated with *level of incivility*, which is statistically significant at the 5% level. Again, this supports Hypothesis 2.

The results of the regression analyses using the normal dataset and measurement 2 are presented in Figure 3. The results provide no evidence that *like-mindedness* has a statistically significant effect on the *level of incivility* at the 5% level. However, the fact that a coefficient is not statistically significant does not prove that there is no effect. Finally, as shown in Figure 4, the results of the regression analyses using the initially civil dataset and measurement 2 show that *like-mindedness* is significantly associated with the *level of incivility* at the 5% level. These results support Hypothesis 2.

Figure 1: Analysis using the Normal Dataset and Measurement 1

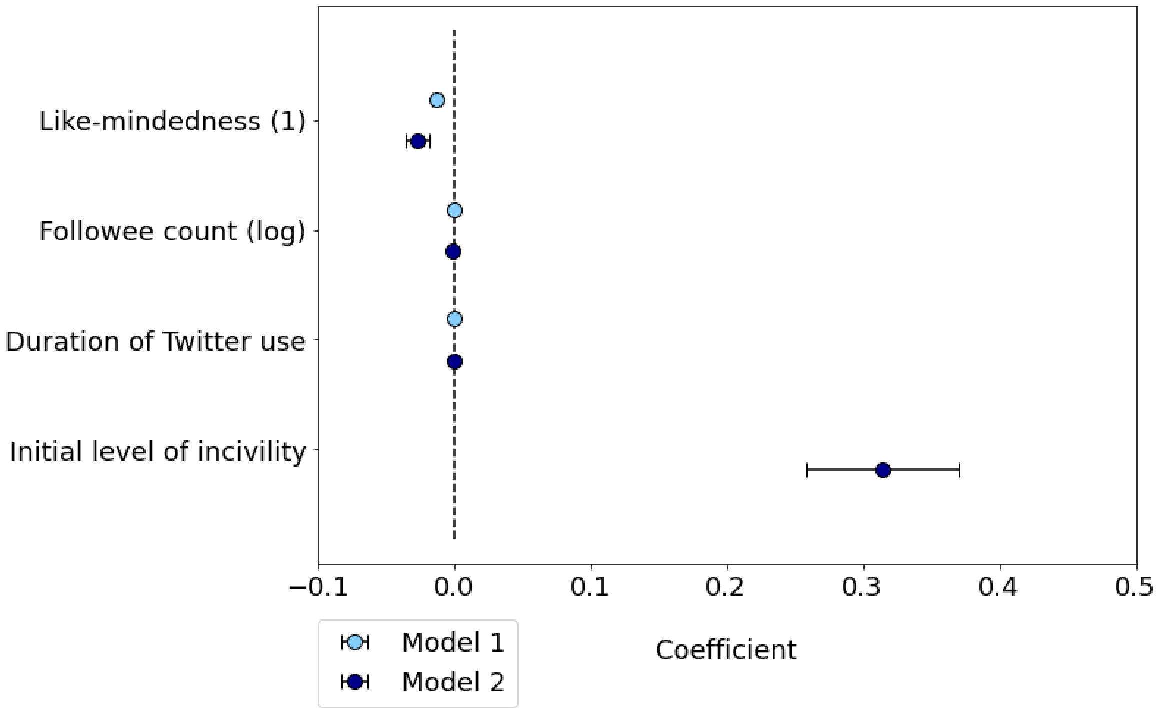


Figure 2: Analysis using the Initially Civil Dataset and Measurement 1

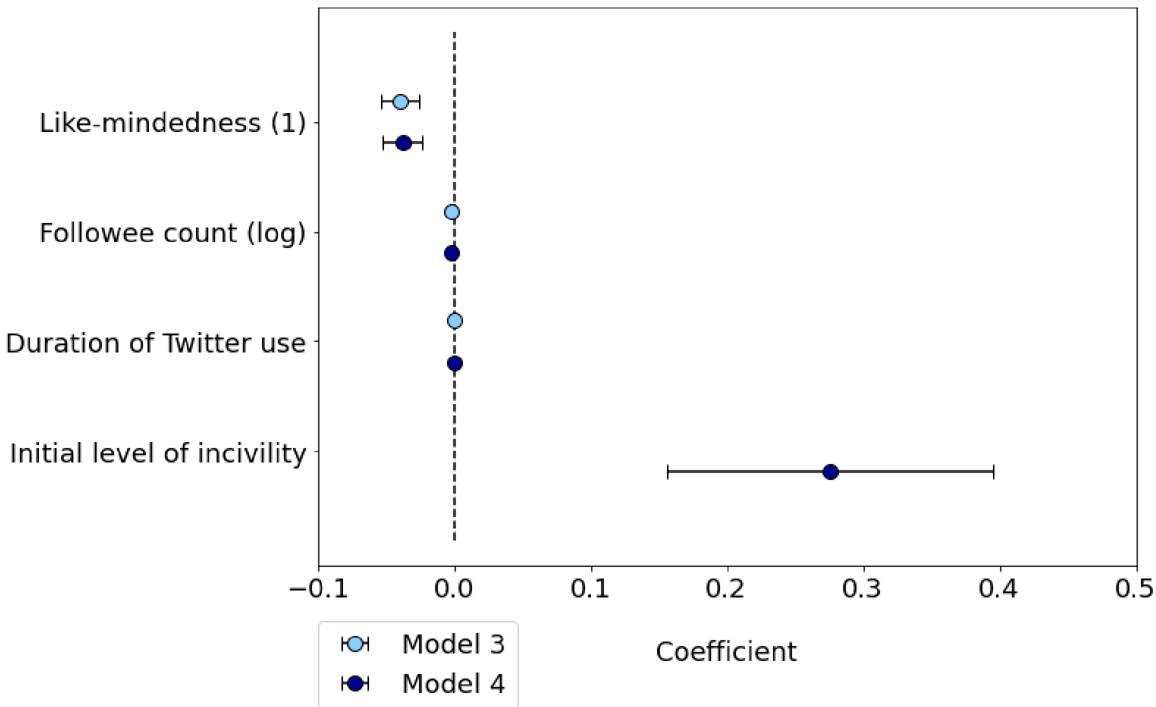


Figure 3: Analysis using the Normal Dataset and Measurement 2

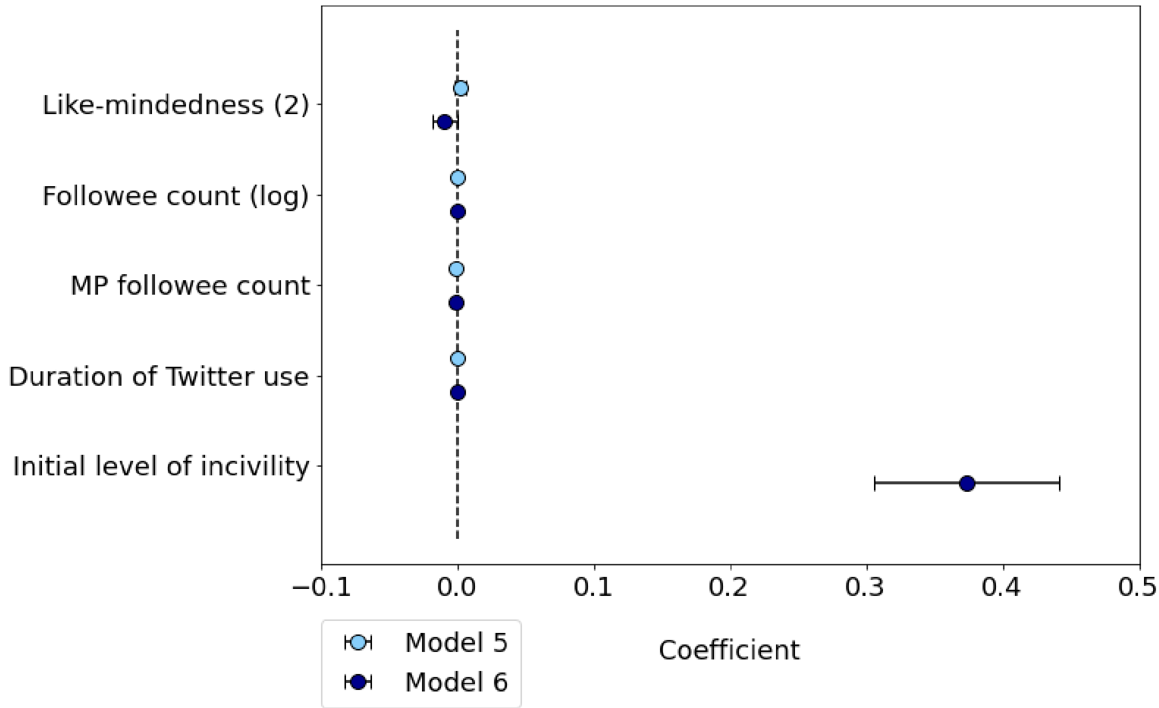
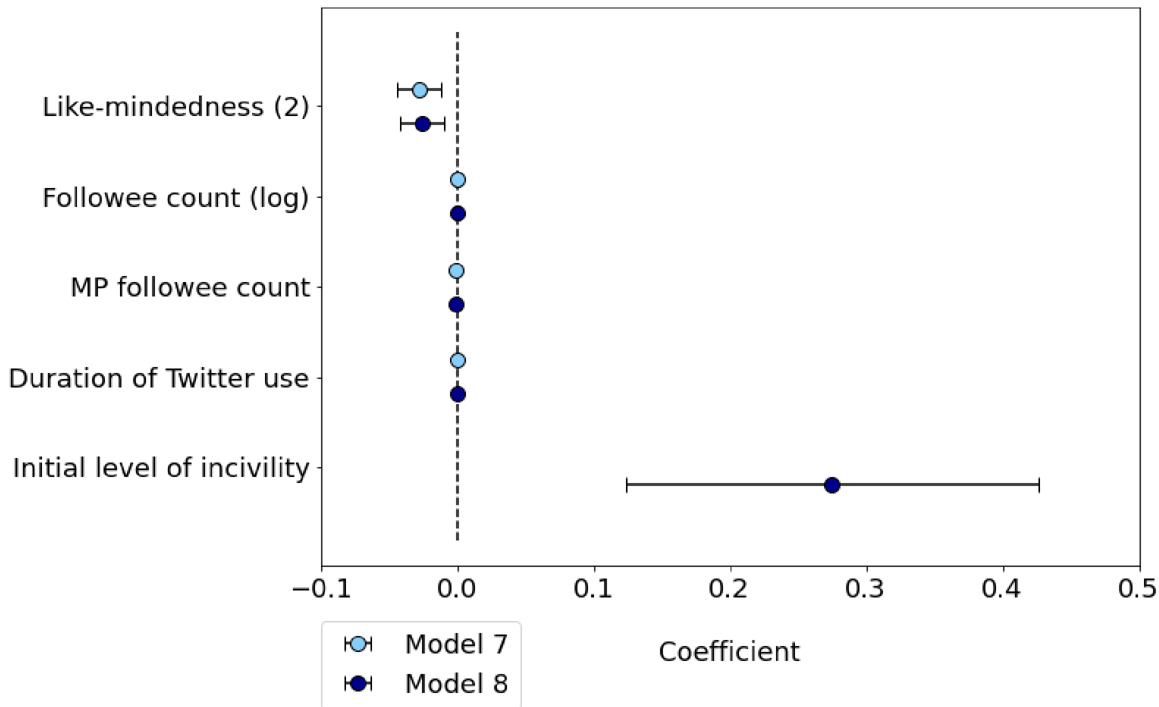


Figure 4: Analysis using the Initially Civil Dataset and Measurement 2



The above results provide multiple pieces of evidence supporting Hypothesis 2, and no evidence supporting Hypothesis 1. The magnitude of the coefficient is illustrated using Model (4) as an example. Since it is difficult to interpret the substantive meaning of the value calculated using cosine similarity alone, the effect size is evaluated by comparing it to the standard deviations. The coefficient of the effect of *like-mindedness (1)* on *level of incivility* is -0.039, the standard deviation of *like-mindedness (1)* is 0.119, and the standard deviation of the *level of incivility* is 0.030. Thus, when *like-mindedness* increases by an amount equivalent to one standard deviation, the *level of incivility* decreases by an amount equivalent to approximately 1/7 of the standard deviation, which indicates a substantially meaningful effect size.

Discussion

The question of whether exposure to both like- and non-like-minded information on the Internet leads to political incivility has not been adequately studied, with previous studies suggesting conflicting answers. Furthermore, there have been insufficient studies on the individual level. This study conducted individual-level analyses using data from Twitter, resulting in more valid findings. The results of the empirical analysis show that, contrary to the findings of a previous study (F. L. Lee et al., 2019), users who are exposed to non-like-minded information on the Internet have higher levels of incivility. Sunstein (2001) proposed that to reduce the opinion polarization caused by the echo chamber phenomenon on the Internet, political web pages should always include a link to a page with opposing views. However, based on the findings of this study, designing a platform that encourages exposure to non-like-minded information may further cause uncivil communication and contribute to more social fragmentation.

This study makes three important contributions to the literature. First, it provided new insights that contradicted the findings of previous studies. Two competing hypotheses were considered and empirical evidence contradicting the findings of a previous study was found. Second, I conducted the analysis at the individual level, whereas in previous studies, the unit of analysis was not at the individual level. Therefore, they could not eliminate the effect of platform culture and the possibility of ecological fallacy. This study was able to avoid these problems because it analyzed individuals on the same platform. Third, it expands the regional scope of political incivility research. To the best of my knowledge, this is the first study to explore the factors of political incivility in the Japanese language.

This study has some limitations. First, it is unclear whether similar results can be found in other languages and cultures. Second, it is also unclear whether the same causal relationship can be observed on other platforms such as Facebook and Instagram. Third, since this study conducted regression analyses using observational data at one time point, the possibility of endogeneity cannot be completely avoided. Therefore, comparative analysis using datasets from multiple languages, cultures, and platforms, as well as analysis using more sophisticated research designs, need to be considered in future studies.

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Appendix

Table 3: Descriptive Statistics

	Mean	Std.	Median	Min	Max
Like-mindedness (1)	0.210	0.119	0.212	-0.298	1.000
Like-mindedness (2)	0.903	0.144	1.000	0.500	1.000
Level of incivility	0.042	0.030	0.042	-0.183	0.301
Initial level of incivility	0.024	0.022	0.026	-0.146	0.120
Followee count	1224.521	8649.132	400.000	1.000	997812.000
MP followee count	10.952	18.067	5.000	0.000	374.500
Duration of Twitter use	1916.653	1445.069	1689.750	0.000	18577.000

Table 4: Analysis using the Normal Dataset and Measurement 1

	Dependent variable:	
	Level of incivility	
Model	1	2
Like-mindedness (1)	-0.012^{*}	-0.026^{*}
	(0.002)	(0.005)
Followee count (log)	0.000	-0.000
	(0.000)	(0.000)
Duration of Twitter use	-0.000^{*}	-0.000
	(0.000)	(0.000)
Initial level of incivility		0.315^{*}
		(0.029)
Intercept	0.046^{*}	0.040^{*}
	(0.001)	(0.002)
Observations	15,591	2,824
Note:		*p<0.05

Table 5: Analysis using the Initially not Uncivil Dataset and Measurement 1

	Dependent variable:	
	Level of incivility	
Model	3	4
Like-mindedness (1)	-0.039^{*}	-0.038^{*}
	(0.007)	(0.007)
Followee count (log)	-0.002^{*}	-0.002^{*}
	(0.001)	(0.001)
Duration of Twitter use	-0.000	0.000
	(0.000)	(0.000)
Initial level of incivility		0.275^{*}
		(0.061)
Intercept	0.051^{*}	0.049^{*}
	(0.003)	(0.003)
Observations	1,279	1,279
Note:		*p<0.05

Table 6: Analysis using the Normal Dataset and Measurement 2

	Dependent variable:	
	Level of incivility	
Model	5	6
Like-mindedness (2)	0.002	−0.009
	(0.002)	(0.005)
Followee count (log)	0.000	0.000
	(0.000)	(0.001)
MP followee count	−0.000*	−0.000*
	(0.000)	(0.000)
Duration of Twitter use	−0.000*	0.000
	(0.000)	(0.000)
Initial level of incivility		0.374*
		(0.034)
Intercept	0.041*	0.039*
	(0.002)	(0.006)
Observations	12,046	1,888
Note:		*p<0.05

Table 7: Analysis using the Initially not Uncivil Dataset and Measurement 2

	Dependent variable:	
	Level of incivility	
Model	7	8
Like-mindedness (2)	−0.028*	−0.026*
	(0.008)	(0.008)
Followee count (log)	0.000	0.000
	(0.001)	(0.001)
MP followee count	−0.000*	−0.000*
	(0.000)	(0.000)
Duration of Twitter use	0.000	0.000*
	(0.000)	(0.000)
Initial level of incivility		0.275*
		(0.077)
Intercept	0.060*	0.057*
	(0.009)	(0.009)
Observations	760	760
Note:		*p<0.05