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Power Harassment Judgement Method Based on Emotion Analysis Using Natural Language Processing

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Abstract

In recent years, the number of power harassment cases in Japan has been increasing. Power harassment is defined as behavior that meets all three of the following criteria: first, it is behavior that is based on a superior relationship; second, it is behavior that is unnecessary and beyond the reasonable scope of work; and third, it is behavior that is detrimental to the work environment. The purpose of this study is to notify the perpetrator when the possibility of power harassment is judged to be high based on the conversational voice. As a preliminary step toward this goal, we experimented to determine whether the target text constitutes power harassment or not using emotion analysis by natural language processing. The system for sentiment analysis in Japanese was built based on Mecab and CaboCha. The polarity dictionary required for the sentiment analysis was created using the FastText natural language processing model based on text data from past cases of power harassment. As a result, a discrimination rate of about 84% was obtained. This is a better result than previous studies. If this system is put into practical use, it could reduce power harassment, which has become a social problem in Japan.

1. Introduction

Power harassment in the workplace has become a social problem in Japan. Power harassment is defined as behavior that meets all three of the following criteria:

- It is behavior that is based on a superior relationship.
- It is behavior that is unnecessary and beyond the reasonable scope of the job.
- It is behavior that is detrimental to the work environment.

For example, a supervisor may verbally abuse a subordinate more than necessary in response to the subordinate's failure. Fig. 1 shows the number of consultations regarding power harassment. According to a survey by the Ministry of Health, Labor, and Welfare (MHLW), the number of power harassment consultations in Japan is increasing yearly; in 2019, there were 87570 consultations [1-2]. In addition, the MHLW survey results indicate that many people who have been subjected to power harassment say that they feel angry, frustrated, or anxious or that their motivation for work has decreased as a result of the harassment. From the above, it can be seen that power harassment has a significant negative physical and mental impact on its victims [3].

The negative social effects of power harassment are many. In organizations where power harassment exists, worker morale and morale tend to decline, and productivity and performance deteriorate. It also has a negative impact on the overall health of the organization, such as increased employee turnover and misconduct. Other negative effects include an increased likelihood that individuals who are subjected to power harassment will face mental health problems such as stress, anxiety, and depression.

Power harassment also has legal aspects. Major examples include violations of labor laws and liability for compensation. Power harassment is an important issue that affects not only individuals and organizations, but society as a whole. Along with legal regulations, appropriate awareness-raising and countermeasures are necessary.

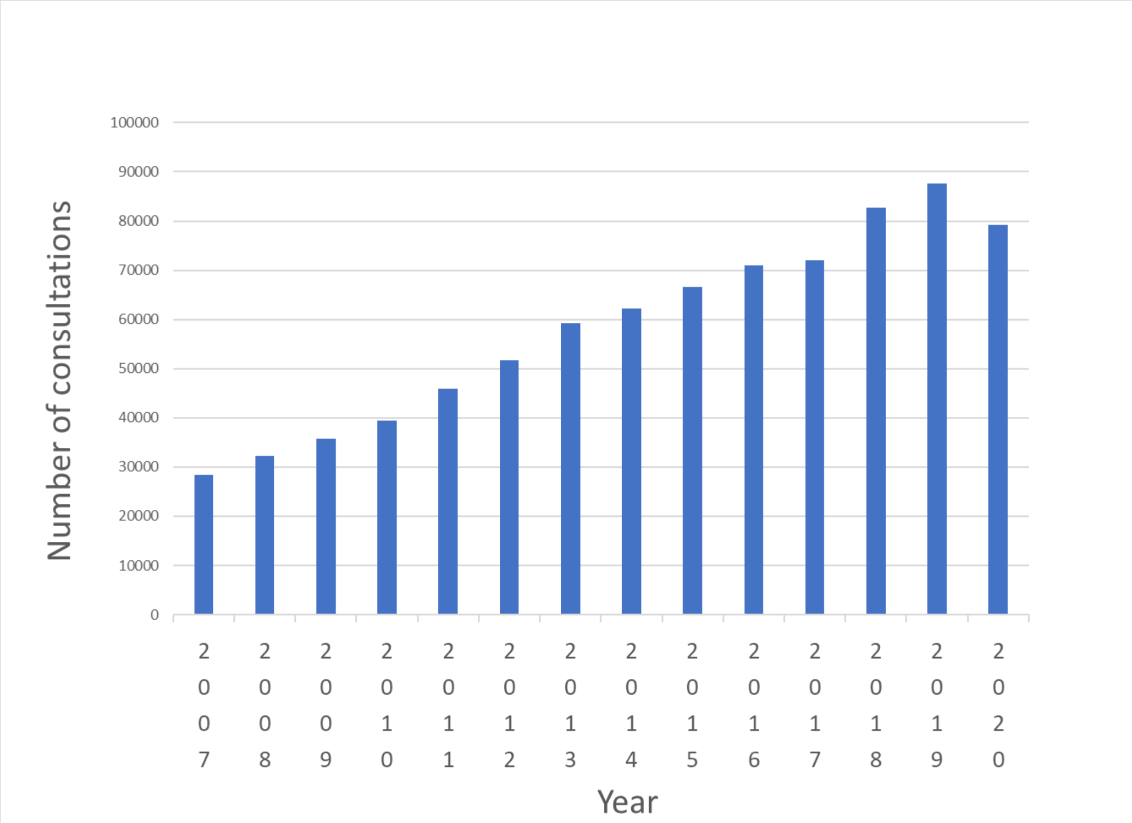

Fig. 1 *Number of power harassment consultations*

Power harassment can be broadly divided into six types. Power harassment can be broadly classified into six categories:

- "Physical aggression" such as violence.
- "Psychological aggression" such as abusive language and unnecessary reprimands.
- "Detachment from relationships" such as ignoring or intentionally isolating an employee.
- "Excessive demands" include giving an employee more work than they can do.
- "Excessive demands" such as giving no work at all.
- "Invasion of privacy" refers to invading an employee's privacy.

The "individual infringement" is categorized into three types. According to a survey by the Ministry of Health, Labor and Welfare, "mental aggression" accounted for the highest percentage at 74.5%. This result indicates that among power harassment, harassment with vague criteria such as "mental aggression" is more prevalent than harassment with visible criteria such as "physical aggression."

According to the Ministry of Health, Labor and Welfare's 2020 survey on "Challenges in Promoting Efforts to Prevent and Resolve Power Harassment," "It is difficult to determine whether or not it is harassment" was the highest response rate at 65.5%. In addition, according to the power harassment Prevention Law, which went into effect in June 2020, the standard for power harassment is "verbal or physical conduct in the workplace based on a superior relationship that goes beyond what is necessary and reasonable in the workplace and that harms the worker's work environment." Because this standard is ambiguous, it is difficult to determine whether or not it is power harassment. This may also be due to the background of other rampant harassment with ambiguous criteria, such as "mental aggression" [3].

Against this background, there is a possibility that power harassment is committed without the perpetrator being aware of it. Therefore, we devised a system that determines whether a statement made by a perpetrator is power harassment and immediately notifies the perpetrator if the statement is applicable. There are four main factors in judging power harassment. These are the voice, such as tone and volume, facial expression of the harasser, psychological state of the victim, and text content. In this study, we attempted to determine whether or not power harassment occurred by focusing on the text. We experimented to determine whether the target text was power harassment using natural language processing based on the text data of past court cases that resulted in power harassment

2. Related Technologies

2.1 Related Research

Related research on power harassment determination systems is presented. A system to determine power harassment using Bidirectional Encoder Representations from Transformers (BERT) was previously built. This model is a binary classification model that determines whether input text is power harassment or not. BERT is a large-scale natural language processing model based on Transformer published by Google in 2018 [4-5]. The model consists of BERTBASE (L=12, H=768, A=12, total number of parameters=110M). where L is the number of Transformer layers, H is the dimensionality of input-output vectors, and A is the number of self-attention heads. The proposed method determines whether a text constitutes power harassment by calculating the similarity (cos-similarity) between the target text and the precedent text and comparing it to a threshold value set through experiments. The similarity is calculated from a 768-dimensional feature vector obtained from each text's BERT hidden layer. Juman++" was used as the morphological analyser, and the "BERT Japanese Pre-trained Model" was used as the pre-trained model. The evaluation results showed that the discrimination rate was about 81% [6].

A related study on sentiment analysis of Japanese sentences using a sentiment word dictionary is introduced. The Japanese sentiment analysis system developed in this study consists of two subsystems: an emotion dictionary management system (EDMS) that generates an emotion dictionary from emotion word data. The other is the Emotional Expression Analysis System (EEAS), which implements an algorithm for fast analysis of emotions in free-text sentences based on the emotional word dictionary. The system analyses which of the ten emotion lists [happy, angry, sad, scared, ashamed, good, disgusted, excited, relieved, surprised] is closest to the emotion value. For example, it is possible to analyse the emotional state of participants in a lecture in real-time and reflect it in the lecture's content based on the sympathetic content, etc. [7].

2.2 About Emotional Analysis

In this study, we implemented a system that applies emotion analysis, a natural language processing technology, and experimented to determine power harassment. Emotion analysis is a technology that analyses sentences and quantifies the degree of emotion in a sentence. Specifically, the emotion analysis model is used to quantify sentences' degree of positivity and negativity as an emotion score. Based on the emotion score, it is also possible to classify whether the sentence is negative or positive. There are several Japanese sentiment analysis methods, such as using a sentiment dictionary to detect sentiment from words included in the analysis target or using a corpus with sentiment labels and machine learning with SVM or deep learning to perform sentiment analysis. In this study, we applied dictionary-based emotion analysis using an emotion dictionary to construct a system. We chose this method because it can be adapted to specific tasks by reorganizing the emotion dictionary. In addition, it can be done with a smaller amount of data compared to supervised learning and deep learning [8].

The algorithm for dictionary-based emotion analysis is shown in Fig. 2. Describe in detail. First, the text is parsed. Syntactic analysis enables a detailed analysis that considers the relationship between morphemes. Second, idiomatic phrases are analysed using a polarity dictionary. A polarity dictionary is one in which words and phrases are assigned a numerical value, called positivity, ranging from -1 to +1. Then, the word is analysed using the polarity dictionary. Here, polarity change words such as "big" are explored, and adverbs such as "quite" are assigned a weight. Then, the word is examined to see if it contains a negative word. If a negative word is included, the positivity of the word is inverted, and a numerical value is assigned. Finally, the positivity of the input text is calculated from the values assigned so far. The positivity of the input text is the sum of the positivity of the words and idioms divided by the number of morphemes [9-13].

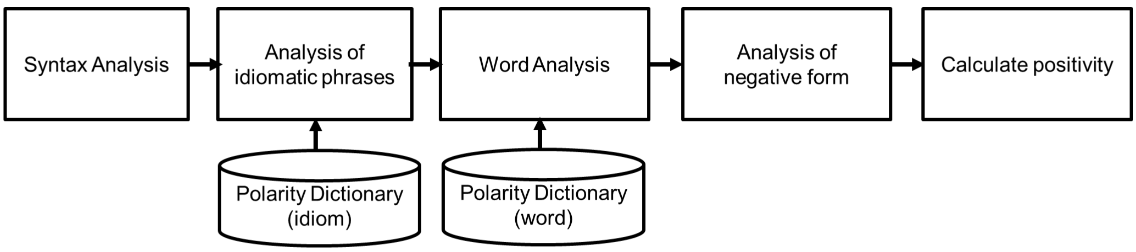

Fig. 2 *Algorithm for sentiment analysis in Japanese (dictionary-based)*

3. Methods

3.1 Proposed Method

As a newly proposed method, we devised a system that measures the "degree of power harassment" with a construction system that applies sentiment analysis of natural language processing technology and notifies the perpetrator when the threshold set through experiments is exceeded. This model is a binary classification model that determines whether the input text is power harassment or not. The "degree of power harassment" is measured in the range of +1 to -1, with a value close to -1 indicating power harassment and a value close to +1 indicating complimentary language. The algorithm of the proposed method is shown in Fig. 3. The upper row is an overview of the proposed method. The middle part is the system's algorithm for measuring the "power harassment degree," which was constructed based on the flow of sentiment analysis. The lower part is the algorithm of the generation method of the "power harassment dictionary" used to measure the "power harassment degree."

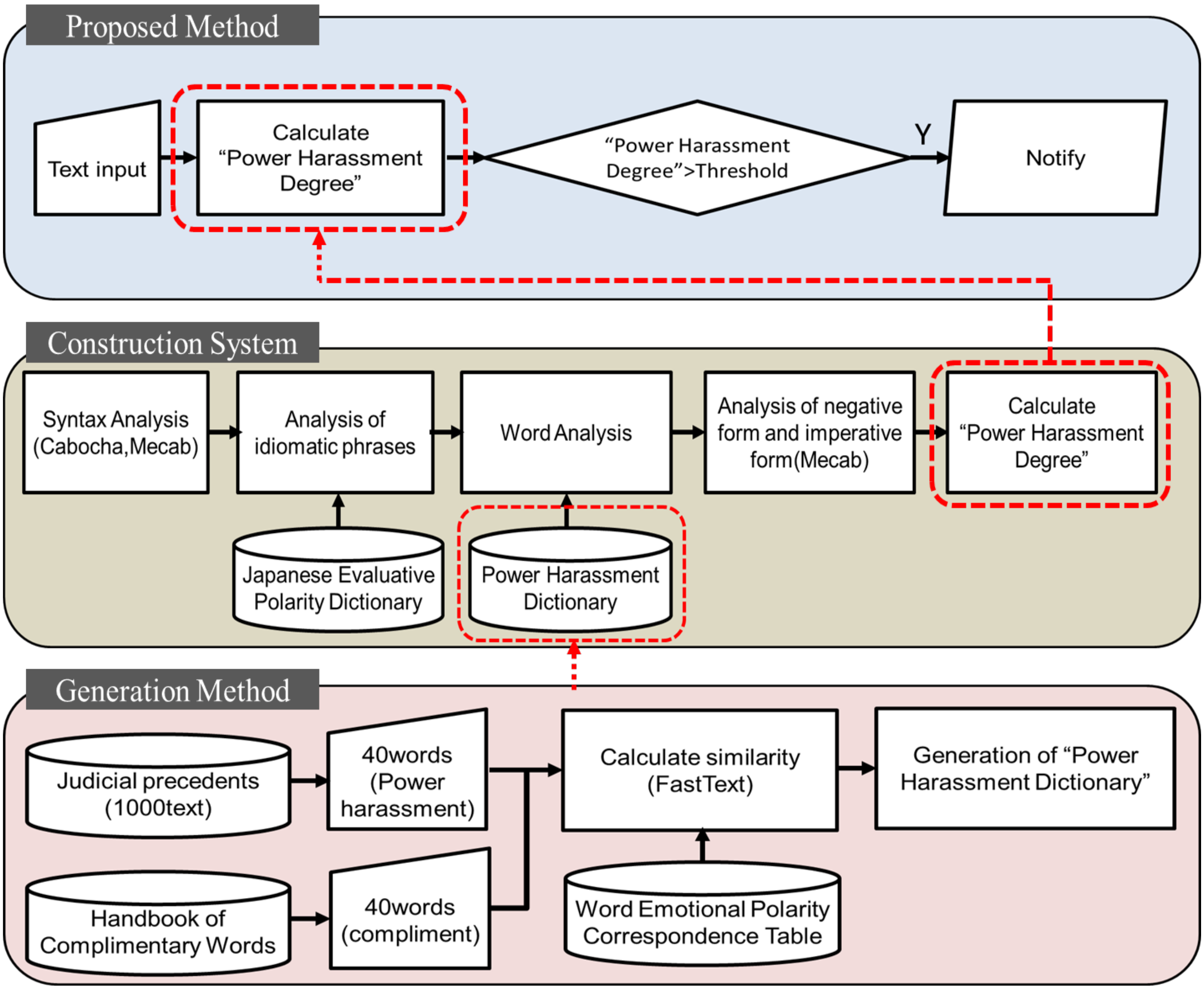

Fig. 3 *Algorithm of the proposed method*

3.1.1 "Power Harassment Degree" Measurement System

Describe the details of the algorithm for the construction system in the middle section of Fig. 3. First, the input text is parsed using Mecab, a morphological analyzer, and CaboCha, a syntactic analyzer. Mecab is an open-source morphological analysis engine developed by the Graduate School of Informatics, Kyoto University [14]. Its essential policy should be designed to be general-purpose and independent of languages, dictionaries, and corpora. It uses Conditional Random Fields (CRF) for parameter estimation, which improves performance compared to hidden Markov models used by other models [15]. CaboCha is a Japanese dependency parser based on Support Vector Machines (SVMs) developed by Taku Kudo from the Nara Institute of Science and Technology

[16]. It applies PKE, a method for speeding up the SVM classification algorithm. It also has the feature that the user can perform training if the data is prepared [17-18].

Second, we use the "Japanese Evaluative Polarity Dictionary" to analyze whether or not idiomatic phrases corresponding to power harassment are included. The "Japanese Evaluative Polarity Dictionary" is a collection of idioms created by the Inui/Okazaki Laboratory of Tohoku University. The contents are manually checked data with evaluation polarity assigned to approximately 8500 expressions [19-21].

Then, whether the words that correspond to power harassment are included is then analyzed using a "power harassment dictionary" of our creation. The method of generating the "power harassment dictionary" is explained in detail in Paragraphs 3-1-2.

Then, Mecab is used to analyze whether it contains negative words and imperative forms.

Finally, the degree of power harassment of the input text is calculated based on the values assigned so far. The rules for measuring the degree of power harassment for each phase are as follows.

• Analysis of idiomatic phrases: If the word contains an idiom considered power harassment, assign -1 to the idiom. If the idiom has a complimentary phrase, the idiom is given +1.

• Word Analysis: Assigns a power harassment degree to the corresponding word. If the word contains the related polarity change word, the “power harassment degree” is inverted, and a numerical value is assigned.

• Analysis of negative form: If a negative word is included, a numerical value is assigned by inverting the "degree of harassment" of the word. If an imperative form is included, -1 is given to the corresponding word.

• Calculate positivity: The sum of the “power harassment degree” of words and idioms divided by the total number of morphemes with “power harassment degree” is the “power harassment degree” of the input text.

3.1.2 How to Generate a "Power Harassment Dictionary

The details of the algorithm for the "power harassment dictionary" generation method are described in the lower part of Fig. 3.

First, we prepared 40 words, each related to power harassment and words of compliments. The words related to power harassment were selected based on the past case precedents that resulted in power harassment. Data analysis was conducted on approximately 900 texts of court precedents, and words were selected based on their frequency of occurrence and connotations. Words of praise were selected based on the "Handbook of Complimentary Words" by Masato Honma. The Handbook of Complimentary Words is a book by Homma that contains words and phrases related to complimentary language in the workplace [22].

Second, the similarity (-1 to +1) between these words and the words in the "Word Emotional Polarity Correspondence Table" was measured using FastText. The "Word Emotional Polarity Mapping Table" is a mapping table of Japanese words and their emotional polarity created by Takamura et al. at Nara Institute of Science and Technology. Emotional polarity is a binary attribute that indicates whether a word has a generally positive or negative impression. The sentiment polarity value is automatically calculated using the lexical network. The closer to -1, the more negative, and the closer to +1, the more positive [23][24]. FastText is a neural network algorithm devised for text classification presented by Armand's Facebook artificial intelligence team. FastText uses a hash function to replace words with vectors of a specified size, thereby enabling text classification. In the tag prediction task for many texts, fastText produced an even percentage of correct answers compared to convolutional neural networks and other neural network-based methods. It was also reported that the time required to build a discriminative model from training data and apply it to test data was concise compared to other methods [25-26].

Finally, the measured similarity was assigned to each word as a “power harassment degree” to be used as a "power harassment dictionary." This gives a value close to -1 for power harassment connotations and close to +1 for complimentary connotations [27].

3.2 Experimental Methods

3.2.1 Dataset

In this study, we collected approximately 150 cases of power harassment precedents from the websites of courts and the Ministry of Health, Labor, and Welfare and extracted around 1000 texts [28][29]. These 1000 texts were randomly split in the ratio of 900:50:50, and each was used as data for generating the "power harassment dictionary" for the model, determining threshold values, and evaluating. Dataset1 was used for threshold determination, and Dataset2 was used for evaluation. In addition, 50 texts of daily conversation were added to Dataset1 and Dataset2, respectively. The daily conversation texts were self-made.

3.2.2 Threshold Determination Methods

From Fig. 3, after measuring the “power harassment degree” of the target text, it is necessary to set a threshold value to determine whether the text is power harassment or not. The threshold was set to be the threshold at which the “power harassment degree” was measured by the construction system for 100 texts in "Dataset1," and the F-measure used as the prediction performance of the machine learning model was the highest. The TP, FP, FN, and TN required to derive the F-measure in light of this study are shown below in Table 1.

Table 1 *Relationship between TP, FP, FN, and TN in this study*

	Predicted not to be power harassment	Predicted to be power harassment
Determined not to be power harassment	TP	FN
Determination of being power harassment	FP	TN

3.2.3 Evaluation Method

The threshold values determined from the Dataset1 results are used for evaluation. The “power harassment degree” was measured by the construction system for 100 texts in Dataset2. The predictive performance of the machine learning model used to derive Accuracy (percentage of correct answers), Precision (percentage of fit), Recall (percentage of reproduction), and F-measure (harmonic of Precision and Recall average) were derived and evaluated [6]. Each of the derivation methods is shown below (1)-(4). These were derived by calculating the number of texts for TP, FP, FN, and TN based on Table 1.

$$\text{Accuracy} = \frac{TP + TN}{TP + FP + TN + FN} \tag{1}$$

$$\text{Precision} = \frac{TP}{TP + FP} \tag{2}$$

$$\text{Recall} = \frac{TP}{TP + FN} \tag{3}$$

$$\text{F} - \text{measure} = \frac{2 * Precision * Recall}{Precision + Recall} \tag{4}$$

4. Results and Discussion

Fig. 4 and Fig. 5 show the graphs representing the “power harassment degree” for each text in Dataset1 and Dataset2, respectively. The vertical axis is the “power harassment degree” and the horizontal axis is the text number after the “power harassment degree” is arranged in ascending order. From the Dataset1 results in Fig. 4, the threshold for the highest F-measure was -0.0084. The results in Fig. 5 also show that many texts are correctly judged when the threshold value is -0.0084.

The TP, FP, FN, and TN numbers for "Dataset1" and "Dataset2" when the threshold is -0.0084 are summarized below as Tables 2 and 3, respectively. The results in Tables 2 and 3 show that the text predicted as power harassment is correctly determined. However, we also found that there were many FPs. In other words, many texts misjudged daily conversation texts as power harassment.

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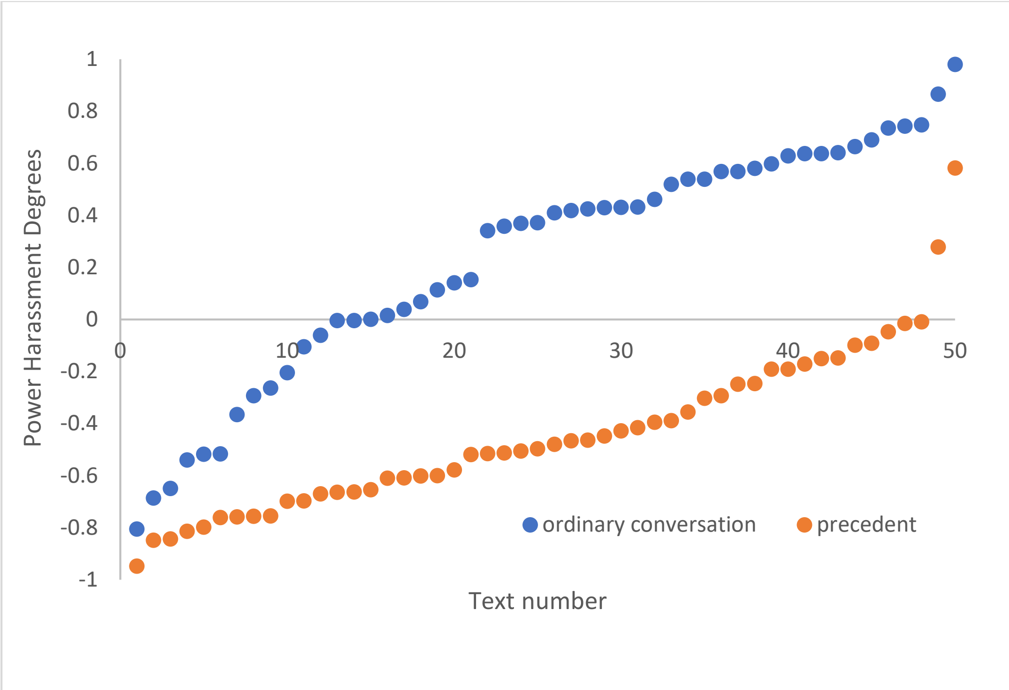

Fig. 4 *"Power harassment degree" by text (Dataset1)*

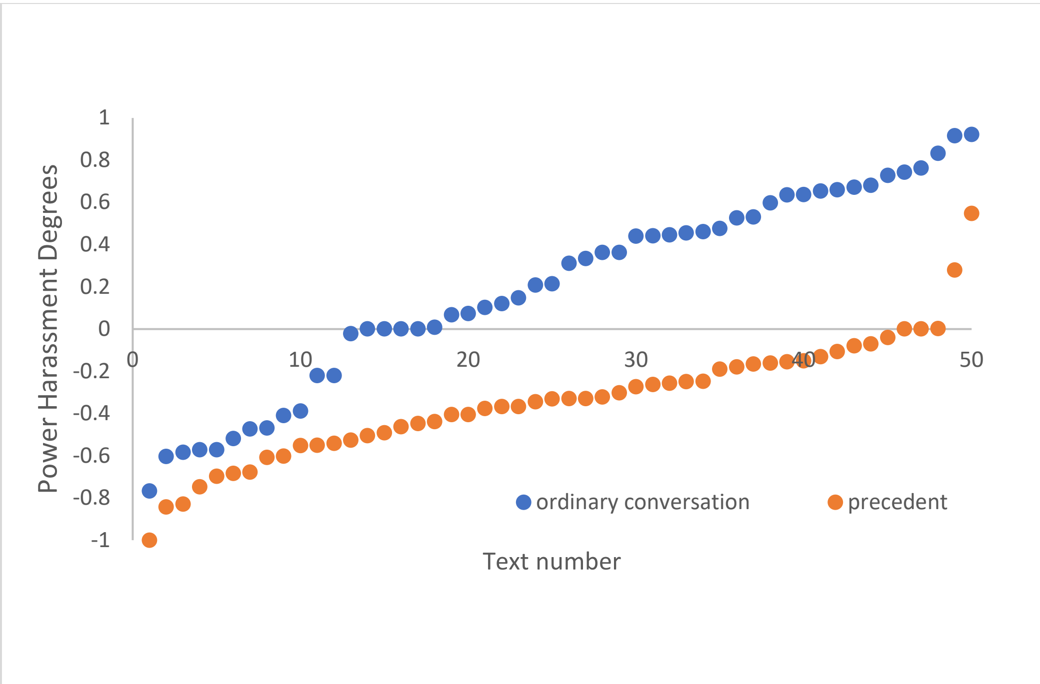

Fig. 5 *"Power harassment degree" by text (Dataset2)*

Table 2 *Number of TP, FP, FN, TN when the threshold is -0.0084 (Dataset1)*

Dataset1		Predicated label	
		Positive	Negative
True label	Positive	38(TP)	2(FN)
	Negative	12(FP)	48(TN)

Table 3 *Number of TP, FP, FN, TN when the threshold is -0.0084 (Dataset2)*

Dataset2		Predicated label	
		Positive	Negative
True label	Positive	37(TP)	5(FN)
	Negative	13(FP)	45(TN)

The evaluation methods used in this study were accuracy, recall, precision, and F-measure, which are used in machine learning prediction performance. Table 4 summarizes the results and is presented below. Table 4 shows that the F-measure for Dataset1 was about 0.87, and the F-measure for Dataset2 was about 0.84, which is higher accuracy than in the previous study [6]. The last research used BERT to vectorize sentence units and measure their similarity to power harassment case texts. This study obtained higher accuracy than the previous study because the analysis was performed in more detailed units, such as words and idiomatic phrases. The processing time was also better than that of the previous research. While the previous study took about 3 seconds for one text, this study took 0.5 seconds. In other words, we achieved an approximately six times faster processing speed. This can be attributed to the calculations being less complex than in the previous study. In the last survey, judgments were made by measuring the similarity to the text of court precedents. In other words, the judgment required deep learning by AI, which took a long processing time. In this study, decisions were made using a small number of libraries, such as Mecab and CaboCha, which has made it possible to achieve a short processing time.

However, a problem was also observed: the Precision value needed to be higher. This was attributed to the large number of FPs. Some words were not assigned a suitable "power-law degree." For example, there were words with “power harassment degree” that differed from human sensitivity, such as "cut" at -0.8423 and "sarcasm" at 0.7723. This may be because the words selected to create the "power harassment dictionary" were inappropriate.

Data bias should also be discussed. Since this study was judged on 100 texts, the data is considered to be biased to a small extent. It is considered necessary to collect more texts and demonstrate comprehensiveness.

Table 4 *Evaluation results of the constructed system (Dataset1, Dataset2)*

	Accuracy	Recall	Precision	F-measure
Dataset1	0.8600	0.9600	0.8000	0.8727
Dataset2	0.8200	0.9000	0.7758	0.8411

5. Conclusion

This paper focuses on power harassment in the workplace in Japan, devises a system to notify the perpetrator immediately, and discusses the evaluation results. The environment in which the system is used is assumed to be one in which each individual carries a device in which the system is installed. This system can also be installed in in-house e-mail tools. In this study, we attempted to determine whether power harassment is power harassment by focusing on the text. If this system is put into practical use, it will serve as evidence of power harassment and will suppress further power harassment on the perpetrator's part. In this study, we determined whether or not the incident constituted power harassment by using a construction system based on emotion analysis. Experiments were conducted to evaluate the identification rate of this system, and better results were obtained in terms of processing time and identification rate than with conventional methods.

However, there were some problems, such as low Precision and the measurement of “power harassment degree” in which certain words differ from human sensitivity. The reason may be that the words selected for creating the "power harassment dictionary" were inappropriate. In the future, we plan to conduct experiments by changing the phrase chosen when creating the "power harassment dictionary" and to conduct a more detailed analysis of the mis-estimated sentences.

This study provides a new perspective on existing methods and a better understanding of the specific phenomenon of power harassment. The proposed model and method are expected to play a fundamental role in future research. In addition, the practical utility of the theory was demonstrated through validation using real data. The findings have direct implications for practice in specific industries and disciplines.

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Conflict of Interest

The authors declare that they have no conflict of interest.

Author Contribution Statement

The authors confirm contribution to the paper as follows: ***study conception and design:*** *Hinari Sasaki, Hironori Uchida, Yujie Li, Yoshihisa Nakatoh;* ***data collection:*** *Hinari Sasaki;* ***analysis and interpretation of results:*** *Hinari Sasaki, Hironori Uchida, Yoshihisa Nakatoh;* ***draft manuscript preparation:*** *Hinari Sasaki, Yujie Li.*

References

[1] Ministry of Health Labour and Welfare (2019). Harassment in data. https://www.no-harassment.mhlw.go.jp/foundation/statistics/
[2] Ministry of Health Labour and Welfare (2021). Enforcement of the Individual Labor Dispute Resolution System. https://www.mhlw.go.jp/stf/houdou/newpage_19430.html
[3] Ministry of Health Labour and Welfare (2021). Survey on Harassment in the Workplace. https://www.mhlw.go.jp/stf/seisakunitsuite/bunya/0000165756.html
[4] A. Vaswani et al. (2017). Attention Is All You Need. http://arxiv.org/abs/1706.03762
[5] Jacob Devlin, Ming-Wei Chang, Kenton Lee & Kristina Toutanava. (2019). BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding, NAACL-HLT,4171-4186. https://doi.org/10.48550/arXiv.1810.04805
[6] Hinari Sasaki, Yoshihisa Nakatoh & Hideaki Kawano (2022). Determination of power harassment Expressions in Conversational Speech Using Natural Language Processing, Human Interaction and Emerging Technologies (IHIET 2022), 241-246. https://openaccess.cms-conferences.org/publications/book/978-1-958651-44-5/article/978-1-958651-44-5_32
[7] Yoshihiro Adachi, Tomohiro Kondo, Takamitsu Kobayashi, Nao Etani & Kaito Ishii. (2021). Emotion Analysis of Japanese Sentences Using Emotion-word Dictionary, Journal of Visualization and Information Science 41 (161), 21-27. https://www.jstage.jst.go.jp/article/jvs/41/161/41_21/_pdf
[8] Hutto, C., & Gilbert, E. (2014). VADER: A Parsimonious Rule-Based Model for Sentiment Analysis of Social Media Text. Proceedings of the International AAAI Conference on Web and Social Media, 8(1), 216-225. https://doi.org/10.1609/icwsm.v8i1.14550
[9] Yui Uozumi, Yuzu Uchida & Kenji Araki (2018). Effectiveness of Emotion Provoking Event Instances for Sarcasm Detection, FIT2018 (17th Forum on Information Technology),163-166. https://www.ieice.org/publications/conference-FIT-DVDs/FIT2018/data/pdf/E-009.pdf
[10] Ryosuke Kurosawa & Tetsuya Sakai. (2022). Estimating the Emotion of New Words Using the Emotional Polarity of Surrounding Words in Tweets, DEIM Forum 2017 C7-3. https://db-event.jpn.org/deim2017/papers/203.pdf
[11] Shinya Morita & Yasuhito Shirai. (2018). Creation and Evaluation of a Field-Specific Emotional Polarity Dictionary, Proceedings of the 80th National Convention Lecture 2018 (1), 317-318. https://www.ipsj.or.jp/event/taikai/80/ipsj_web2018/data/pdf/7P-04.html
[12] Misaki Miwa, Atsushi Tatsuma & Masaki Aono. (2014). Sentiment analysis of tweets focusing on the position of polarity words and on the emphasized and de-emphasized expressions, Proceedings of the Forum on Information Science and Technology 13 (2), 227-228. https://cir.nii.ac.jp/crid/1050292572115130624
[13] Hiroya Takamura, Kashi Inuta & Manabu Okumura. (2006). Emotional Polarity Classification of Multi-word Expressions Using a Hidden Variable Model, Transactions of Information Processing Society of Japan 47 (11), 3021-3031. https://cir.nii.ac.jp/crid/1050564287835940352
[14] Taku, K. (2013) MeCab: Yet Another Part-of-Speech and Morphological Analyzer. https://taku910.github.io/mecab/

[15] Taku Kudo, Kaoru Yamamoto & Yuji Matsumoto. (2004). Applying Conditional Random Fields to Japanese Morphological Analysis, Proceedings of the 2004 Conference on Empirical Methods in Natural Language Processing (EMNLP-2004), 230-237. https://www.semanticscholar.org/paper/Applying-Conditional-Random-Fields-to-Japanese-Kudo-Yamamoto/f16410d241616553ae6e63fcf4ba8959eda58aea
[16] Taku, K. (2015). CaboCha: Yet Another Japanese Dependency Structure Analyzer. https://taku910.github.io/cabocha/
[17] Taku Kudo & Yuji Matsumoto. (2003). Fast Methods for Kernel-Based Text Analysis, Proceedings of the 41st Annual Meeting of the Association for Computational Linguistics (ACL 2003 in Sapporo), 24-31. https://aclanthology.org/P03-1004/
[18] Taku Kudo & Yuji Matsumoto. (2002). Japanese Dependency Analyisis using Cascaded Chunking, In COLING-02: The 6th Conference on Natural Language Learning 2002 (CoNLL-2002). https://aclanthology.org/W02-2016/
[19] Nozomi Kobayashi, Kentaro Inui, Yuji Matsumoto & Kenji Tateishi. (2005). Collecting Evaluative Expressions for Opinion Extraction, Journal of Natural Language Processing 12(3), 203-222. https://www.jstage.jst.go.jp/article/jnlp1994/12/3/12_3_203/_article
[20] Masahiko Higashiyama, Kentaro Inui & Yuji Matsumoto. (2008). Learning Sentiment of Nouns from Selectional Preferences of Verbs and Adjectives, Proceedings of the 14th Annual Meeting of the Association for Natural Language Processing, 584-587. https://dl.acm.org/doi/abs/10.1145/3472307.3484663
[21] Inui-Okazaki Laboratory., Tohoku University (2008). Japanese Sentiment Polarity Dictionary. https://www.cl.ecei.tohoku.ac.jp/Open_Resources-Japanese_Sentiment_Polarity_Dictionary.html
[22] Masato, H & Kyoko, Y. (2013). Handbook of Complimentary Words.
[23] Hiroya Takamura, Takashi Kan, Gaku Okumura (2006) Extracting Emotional Polarity of Words Using Spin Model, Journal of Information Processing Society of Japan 47(2), 627-637. https://cir.nii.ac.jp/crid/1520572359481043200
[24] Hiroya Takamura, Takashi Inui & Manabu, Okumura. (2005) Extracting Semantic Orientations of Words using Spin Model", In Proceedings of the 43rd Annual Meeting of the Association for Computational Linguistics (ACL2005), 133-140. https://aclanthology.org/P05-1017/
[25] Armand Joulin, Edouard Grave, Piotr Bojanowski, & Tomas Mikolov. (2017). Bag of Tricks for Efficient Text Classification. In Proceedings of the 15th Conference of the European Chapter of the Association for Computational Linguistics: Volume 2, Short Papers, 427–431. https://aclanthology.org/E17-2068/
[26] Piotr Bojanowski, Edouard Grave, Armand Joulin, & Tomas Mikolov. (2017). Enriching Word Vectors with Subword Information, Transactions of the Association for Computational Linguistics, 135–146. https://aclanthology.org/Q17-1010/
[27] Kawamura Keita & Yuko Nagana (2022). Recurrent Neural Network Using LSTM and Polarity Dictionary for Sentence Favoritism and Unfavoritism Classification, Proceedings of the 84th National Convention 2022 (1), 679-680. https://cir.nii.ac.jp/crid/1050856970555870080
[28] Court. (2021) Database of Precedents. https://www.courts.go.jp/app/hanrei_jp/search1
[29] Ministry of Health Labour and Welfare. (2018) Major Court Decisions Related to power harassment. https://www.mhlw.go.jp/content/11909500/000548187.pdf