Engineering Approach to Explore Language Reflecting Well-Being

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Abstract

Although well-being is helpful in measuring the state of society from various perspectives, past research has been limited to (1) questionnaire surveys, which make it difficult to target a large number of people, and (2) the major indices focus on individual factors and do not incorporate group factors. To tackle these issues, we collected daily reports from the company employees that included text, their individual subjective well-being, and team subjective well-being. By using the collected data, we constructed a well-being estimation model based on the Large Language Model and examined an indicator called "sharedness index", as a state of the team that influences an individual well-being, measured using both score- and text-based methods.

Introduction

Well-being has drawn considerable attention due to its contributions to physical (Diener et al. 2017) and mental health (Organization 2001), economic prosperity (Diener, Oishi, and Lucas 2003; Deaton 2008), and work performance (McDaid, Park, and Wahlbeck 2019). Although well-being is considered a more reliable indicator of social success than statistical indices, past research has been limited to (1) questionnaire surveys, which make it difficult to target a large number of people, and (2) the major indices focus on individual factors and do not incorporate group factors.

As for (1), for large-scale and real-time measurement, a time-saving method is desirable. In this study, we construct a well-being estimate model from short texts based on a Large Language Model (LLM). In existing studies, well-being has been estimated from textual features (Linguistic Inquiry and Word Count (LIWC) (Pennebaker, Francis, and Booth 2001), n-gram, topic) using basic machine learning models such as multi-layer perceptrons and random forests (Schwartz et al. 2016). In addition, well-being has also been estimated from textual responses to questions about life satisfaction using the Bidirectional Encoder Representations from Transformers (BERT) (Devlin et al. 2018) model (Song and Zhao 2023). However, there have been no attempts to estimate well-being using a transformer-based model based on free-form texts of daily life unrelated to life satisfaction, as in this study.

As for (2), some studies show that what contributes well-being comes not just from themselves but also from the people around them (Fukushima, Uchida, and Takemura 2021; Hitokoto and Uchida 2014; Giorgi et al. 2021). However, how well-being links to the group's psychological condition is not yet widely debated. We hypothesized, based on shared reality (Hardin and Higgins 1996; Echterhoff, Higgins, and Levine 2009) in social psychology, that the degree to which the group psychological condition is shared is a factor that influences individual well-being. Therefore, this study investigates the relationship between the degree to which the group psychological condition is shared and the individual well-being. While there are many possible group psychological conditions, we introduced the concept of SHAREDNESS INDEX and measured it with two types of metrics: (1) score-based metric, that is the consistency of team well-being rated by members, and (2) text-based metric, that is the semantic similarity of free texts entered by members. Text-based metric has the disadvantage of being unstructured and therefore difficult to handle in engineering, but they can be measured without taking a questionnaire, which has significant practical advantages if the indicators are valid.

Data

To examine the hypothesis, we collected daily reports of employees at the Japanese company, for two months, between 1 September and 31 October 2022. 121 employees agreed to participate in the experiment in advance, and 94 of them entered their daily reports one or more times during the two months. The employees belonged to one of the 23 teams. A total of 1,798 daily reports were collected. Note that each team comprised four to seven members, and the number of members who input one or more daily reports ranged from one to seven for each team.

To collect daily reports, we developed a web form using Streamlit[1] (Figure 1). This form had four input fields: diary entry, individual well-being score, team well-being score, and workplace.

This research was approved by Kyoto University after ethics approval, including the Nara Institute of Science and Technology (Review No. 26-P-16). In this research, all methods were performed in accordance with the relevant

[1]https://streamlit.io/

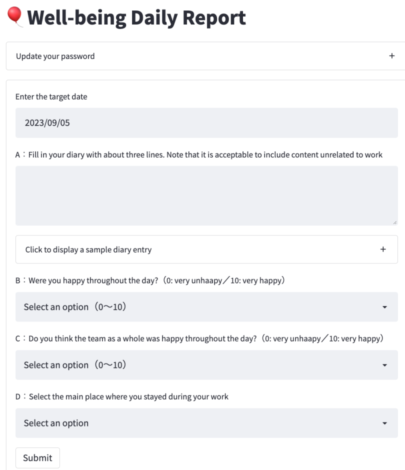

Figure 1: The screenshot of the daily report system.

guidelines and regulations. An informed consent was obtained from all participants.

The following data sources were examined to understand the correlations between the two variables:

Diary entry: A free diary about 3 line. The content does not have to be related to happiness or emotions, nor does it have to be related to work.

Individual well-being score: This represents the individual well-being of participants and was self-reported on an 11-point scale ranging from 0 (unhappy) to 10 (happy).

Team well-being score: This represents the well-being of the team to which the participants belonged and was evaluated by the participants on an 11-point scale ranging from 0 (unhappy) to 10 (happy).

Experiment

(1) Estimating Model

Setting In this experiment, we build a BERT-based estimation model that takes text written by employees as input and outputs an estimated well-being score. The Pearson correlation coefficient, which is also used in the existing study (Song and Zhao 2023), is used as an evaluation metric. The correlation coefficient between the well-being score estimated by the model (estimated well-being) and the well-being score self-reported by employees (reported well-being) is then calculated. As test data for the evaluation, we used 652 daily reports of 11 employees, collected from a different company than the one we used for training.

Result The correlation coefficient between estimated well-being and reported well-being is 0.49 (Figure 2), which is higher than the correlation coefficient of 0.42 in existing studies. The LLM performs better than dictionary-based methods such as LIWC.

(2) Sharedness Index

Setting We employed two evaluation metrics to examine the correlation between sharedness index and individual well-being; the score-based metric and the text-based metric. The score-based metric was defined by the negation of the standard deviation of the team well-being scores of the same team members. Text-based metric was defined by the semantic similarity of diaries among team members calculated using the Word Mover's Distance method (Kusner et al. 2015) based on the pre-trained Word2Vec model (Mikolov et al. 2013), commonly used in natural language processing (NLP). Note that data were divided into weekly units by teams for calculating sharedness index.

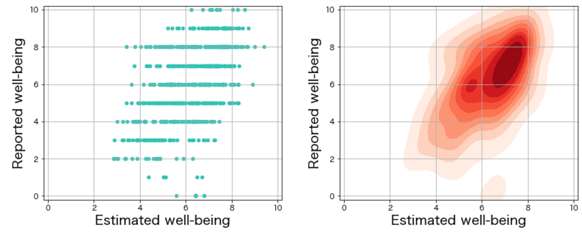

Figure 2: Results for estimate model.

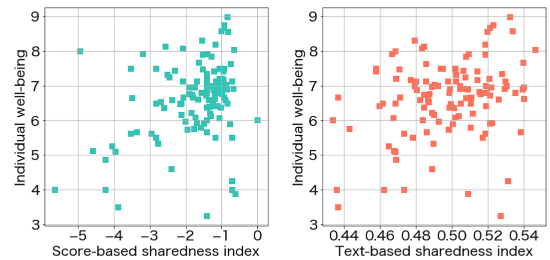

Figure 3: (a) Results for score-based sharedness index. The correlation coefficient is 0.332 (p=0.0002). (b) Results for text-based sharedness index. The correlation coefficient is 0.257 (p=0.003), showing a weaker correlation than score-based sharedness index.

Results The score-based sharedness index and individual well-being indicated a positive correlation coefficient of 0.332 (p=0.0002), as shown in Figure 3(a). The text-based sharedness index showed a correlation coefficient of 0.257 (p=0.003) with individual well-being as shown in Figure 3(b). Both metrics supported the hypothesis.

Conclusion

We constructed an estimation model of well-being from free-form text input and examined the correlation between sharedness index and individual well-being. In both experiments, NLP technology was the key technology, and we believe that NLP technology can be applied beyond our experiments in this study to additional areas of well-being research that have not yet been focused on. In future work, we plan to analyze in detail the linguistic features that contribute to well-being and to verify causal relationships in experimental settings, including interventions.

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