Sensors and Materials, Vol. 36, No. 10 (2024) 4535–4548
MYU Tokyo

S & M 3816

Work Attitude Personal Life Record Collection Platform: A Framework for Daily Mental Health Monitoring of Workers

Kai Suwabe,[1*] Takashi Maegawa,[2] Teruhiro Mizumoto,[3]
Hirohiko Suwa,[2] and Keiichi Yasumoto[2]

[1]Graduate School of Information Science, Nara Institute of Science and Technology,
8916-5 Takayama-cho, Ikoma, Nara 630-0192, Japan
[2]Graduate School of Science and Technology, Nara Institute of Science and Technology,
8916-5 Takayama-cho, Ikoma, Nara 630-0192, Japan
[3]Department of Computer Science, Faculty of Innovative Information Science, Chiba Institute of Technology,
2-17-1 Tsudanuma, Narashino, Chiba 275-0016, Japan

(Received July 1, 2024; accepted August 29, 2024)

Keywords: mental health monitoring, smartphone-based estimation, labor productivity, work engagement, multimodal information

Monitoring mental health is crucial for individuals at work and in other areas of life, as mental states significantly impact both health and labor productivity. Various governments in developed nations have initiated efforts to support workers' mental health, yet traditional methods rely heavily on questionnaires and interviews, which are not feasible for daily monitoring. To address this, we propose the "Work Attitude Personal Life Record (PLR) collection platform," designed to continuously estimate and document "work attitude" (encompassing work engagement and recovery experiences, among other factors) through multimodal information. In this paper, we outline the proposed framework and present the performance of our estimation model on the basis of data collected from preliminary experiments. The findings indicate a positive potential for the feasibility of our approach.

1. Introduction

Maintaining a healthy mental state is crucial for workers to ensure labor productivity. Therefore, many developed countries, including Japan, where workers often endure long hours of work and experience poor health and high levels of stress, are focusing on monitoring workers' mental health and creating healthier work environments. However, the current monitoring methods, which rely on interviews and questionnaires,(1,2) are not designed for daily use.

With the widespread adoption of smartphones, interest has been growing in utilizing mobile devices to monitor users' mental states and promote self-care.(3) Several methods for estimating psychological states using smart devices have been proposed.(4–8) However, many of these methods rely on information from contact devices such as smartwatches, so the requirement to

*Corresponding author: e-mail: kai.suwabe@ubi-lab.com
https://doi.org/10.18494/SAM5216

ISSN 0914-4935 © MYU K.K.
https://myukk.org/

prepare the device and have it in contact with the body every day for daily monitoring places a burden on the user. Additionally, most studies focus primarily on negative indicators such as stress and depression, overlooking positive indicators of workers' well-being. Note that even when stress is present, high motivation and effective recovery from stress mitigate its negative impact.[9] Hence, both positive and negative indicators must be included to maintain workers' mental health.

In response, we propose and develop the "Work Attitude Personal Life Record (PLR) collection platform",[10] which continuously estimates workers' mental states (including work engagement and recovery experiences, collectively termed "work attitude") using only the multimodal information obtainable from smartphones, which are devices that most users carry daily.

In this paper, we describe our proposed method and present the evaluation experiments conducted to investigate its feasibility. Note that these evaluation experiments are preliminary and conducted before a large-scale empirical trial.

Through these experiments, we found that estimates with a sufficient number of samples performed above the chance level. Conversely, estimates with an insufficient number of samples did not yield effective results. Additionally, the results of feature selection indicated that the features used vary depending on the estimation target. These findings positively suggest the necessity and feasibility of conducting large-scale empirical experiments for our proposed method.

Although this work is an extended version of our previous study,[10] in this paper, we describe the design of the Work Attitude PLR collection platform in more detail in terms of the rating scales selected and the structure of the data to be collected. In addition, we discuss ways to improve estimation performance by incorporating new measures in the results of our analyses.

2. Related Work

In this section, we discuss related work on the continuous estimation of work attitude, which is the objective of our research, focusing on methods using questionnaires and smart devices for monitoring psychological states.

2.1 Monitoring psychological states using questionnaires

Quantifying psychological states is crucial for preventing mental disorders such as depression and anxiety and for protecting people's health. Traditional methods often rely on questionnaires to quantify these intangible psychological states. For example, the Affective Lability Scale asks respondents to read statements that describe psychological states and rate how much they apply to themselves, thereby quantitatively assessing mood.[1] Although widely used in clinical surveys, these methods suffer from recall bias and the limitations of individual memory, leading to a lack of immediacy. Ecological Momentary Assessment (EMA) has gained attention as a method of addressing these issues.[11] EMA consists of short questions designed to capture real-time information about human experiences, allowing measurement that is not constrained by time or location, which was challenging with traditional questionnaire-based methods. However, EMA still poses a burden on respondents, necessitating a trade-off between the granularity of data collection and participant burden. As a solution to these problems, research has been conducted to use data collected by smart devices to reduce the burden on respondents while ensuring the quality of measurements.

2.2 Monitoring psychological states using smart devices

Recent research attempts to estimate psychological scales using smart devices have attracted attention. Amenomori *et al.* conducted research on the easy assessment of students' quality of life (QOL) using smart devices, employing biometric and activity data to build QOL estimation models.(4) Jaques *et al.* studied the prediction of students' happiness using smart devices, building a model that estimates composite psychological scales related to happiness, health, energy, and stress using biometric and activity data.(5) Sano *et al.* used wearable sensors and smartphones to collect data and conduct surveys on stress and mental health, estimating Grade Point Average and Pittsburgh Sleep Quality Index scores with classification accuracies ranging from 67 to 92%.(6) Boukhechba *et al.* collected automatic objective sensor data via smartphones and conducted surveys on social anxiety and depression, demonstrating significant correlations between the data and psychological indicators.(7) Fukazawa *et al.* attempted to predict unconscious changes in anxiety in daily life using smartphone sensor logs and application usage data along with the State Trait Anxiety Inventory score, achieving an *F*-value of 74.2%.(8)

These studies have successfully estimated subjective psychological indicators from objective data collected by wearable devices and smartphones to a certain extent. However, the requirement for users to possess specific devices, such as smartwatches or special wearable devices, results in high participation costs. Additionally, most studies focus on negative indicators such as stress and depression, neglecting positive indicators that reflect workers' well-being. Note that even with stress, high work engagement and recovery can mitigate negative impacts,(9) suggesting the need to target both positive and negative indicators to measure work attitude.

To enable daily mental health monitoring, our aim is to continuously estimate work attitude, which includes both positive and negative psychological scales, using only smartphones that many workers possess.

3. Methods

In this section, we describe the Work Attitude PLR collection platform that we proposed to enable continuous mental health monitoring for workers. First, we explain work attitude, the psychological evaluation scale used in this study. Then, we discuss the data collected via smartphones for estimating work attitude. Finally, we present the structure of the Work Attitude PLR collection platform using the aforementioned evaluation scales and data.

3.1 Work attitude

Several psychological scales have been developed for daily mental health monitoring. These scales, unlike occupational stress indices that are usually measured through annual tests, can be used to evaluate mental states using fewer items, thus reducing the burden on respondents. However, as mentioned in the previous section, it is insufficient to assess workers' mental health using only a single psychological scale—both positive and negative aspects need to be evaluated. Although diligently working is important for improving job performance, doing so exclusively may lead to burnout(12)—"a state of exhaustion in which one is cynical about the value of one's occupation and doubtful of one's capacity to perform". (13)

Therefore, in this work, we proposed "work attitude" referring to a work approach that balances labor and recovery comprehensively and adopted three existing scales as pilot scales: work engagement, recovery experience, and recovery status.

For work engagement, we adopted the Japanese version of the Utrecht Work Engagement Scale (UWES-3),(14–16) which evaluates three subscales, namely, vigor, dedication, and absorption, using three items (*WE*1, *WE*2, and *WE*3, respectively). This scale is essential as it relates to workers' productivity.

The recovery experience measure(17,18) evaluates activities during leisure, which help reduce stress levels elevated by work-related stress. It assesses four subscales, namely, psychological detachment, relaxation, mastery, and control, each with four items, totaling 16 items. We referred to existing research(17) and extracted the item with the highest factor loading for each subscale (*RE*1, *RE*2, *RE*3, and *RE*4, respectively) to reduce the burden. Measuring recovery experience is important as chronic high stress levels can increase the risk of developing mental disorders.

Recovery status(19) evaluates the state of recuperation before work, reflecting recovery during leisure time. Adequate recovery before work indicates that physical and psychological resources are available for work, whereas inadequate recovery indicates a resource deficit. This scale evaluates overall recovery, physical recovery, mental recovery, and vigor with four items. We exclude the items for overall recovery and vigor (which overlaps with work engagement) and use two items for physical and mental recovery (*RS*1 and *RS*2, respectively). Additionally, we incorporate a question about sleep quality from the Pittsburgh Sleep Quality Index(20) as another item (*RS*3), as recovery status evaluates recuperation after sleep and is related to sleep quality.(21)

Using these scales, we monitor workers' mental health. Work engagement (*WE*1–3), potentially affected by work, is measured in the evening after work. Recovery experience (*RE*1–4) and recovery status (*RS*1–3), affected by leisure activities and sleep, are measured in the morning before work.

3.2 Data collection via smartphones

To estimate workers' work attitude, this method uses data collected by smartphones. The collected data includes activity data, short self-recorded video data (about 10 s), and questionnaire data. Activity data comprises total distance traveled calculated using GPS and step count, widely used in studies(22) on stress and depressive states due to their relationship with mental states. These data are automatically collected via smartphone applications.

The self-recorded video data involves workers stating a brief message reflecting their current feelings, constituting facial images, voice, and text (spoken content). Facial images can be used to recognize emotions,[23] and voice data has been used to estimate psychological scales related to depression.[24] In this study, we additionally used spoken content for multimodal emotion estimation, potentially revealing relationships with psychological scales not covered in existing research.

Questionnaire data was collected after recording the video to calculate workers' sleep efficiency. This questionnaire was also used to obtain ground truth in the evaluation experiments, the details of which are provided in Sect. 4.

Figure 1 shows the data collection process. Workers record a self-video in the morning after waking up and before heading to work, starting the recording of lifelog data. They record another self-video in the evening before bed, ending the recording of lifelog data. The first phrase in each recording is "Good morning" (morning) and "Good night" (evening), establishing a baseline term. This allows comparing voice quality for the same term. After the baseline term, workers state a brief message (e.g., "I slept well and feel energetic", "I'm still sleepy and don't want to go to work", "I was praised by a client, I did well", or "I got scolded by my boss, I'll sleep it off").

3.3 Work Attitude PLR collection platform

Figure 2 shows the structure of the Work Attitude PLR collection platform. The system comprises smartphones for collecting data and a server for processing and storing this data.

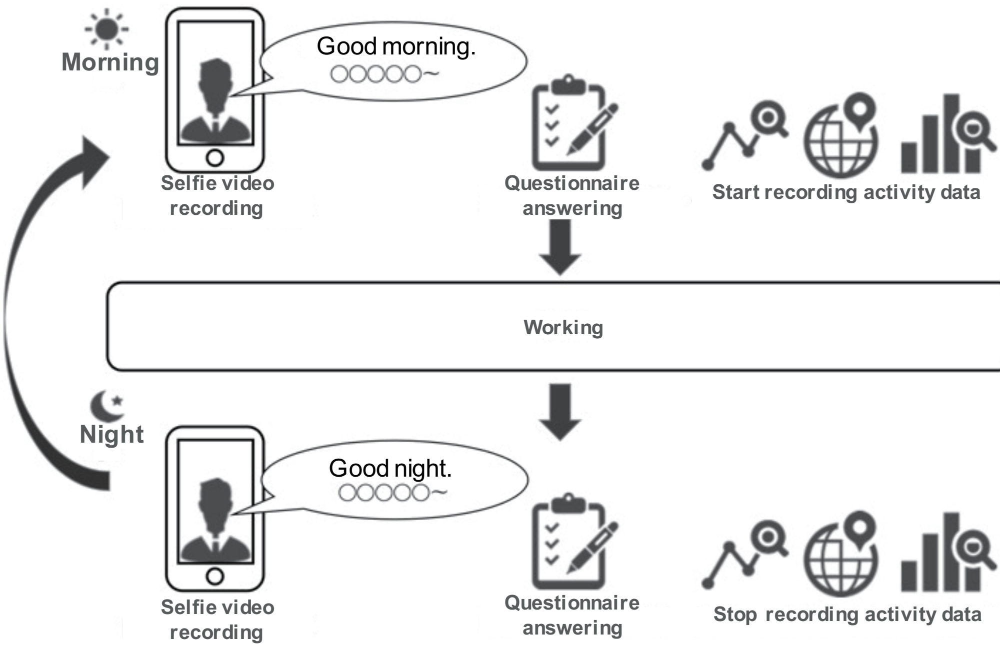

Fig. 1. Workflow of data collection.

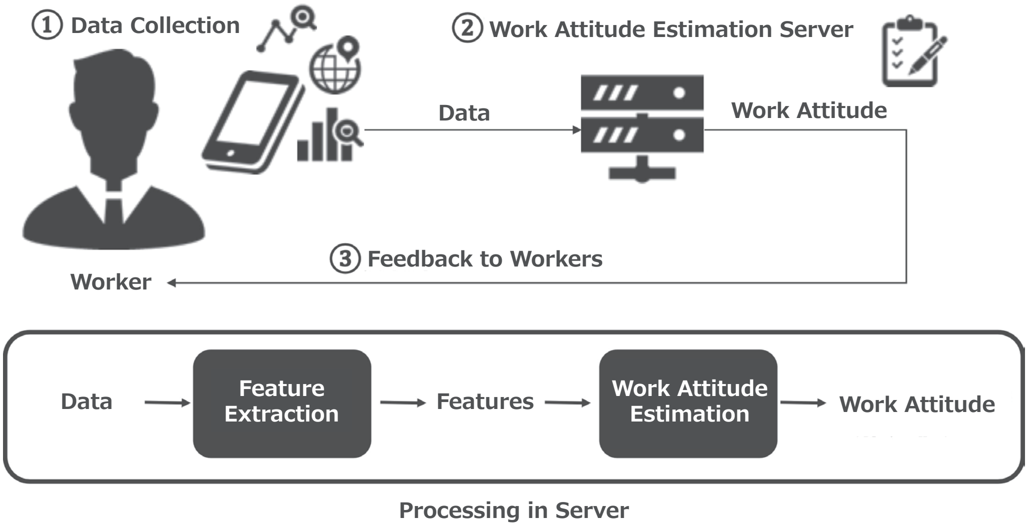

Fig. 2. Overview of Work Attitude PLR collection platform.

Smartphones collect activity data and self-recorded video data from workers and transmit them to the server. The server uses a feature extraction program to extract feature sets from the received data groups, input these features into the work attitude estimation model, and output the estimated work attitude. The estimated work attitude is recorded in a database as a PLR. This estimated work attitude is also fed back to the workers, allowing them to objectively reflect on their work style.

The feature extraction program extracts the daily step count and total movement distance from the activity data as features. From the self-recorded video data, it extracts emotion values from three channels: facial images, voice, and text (spoken content) as features. For emotion value acquisition, we use Face API (Microsoft), Empath API (Empath), and Cotoha API (NTT Communications). For the facial image channel features, five images are extracted from the video, and the average, median, variance, and maximum values of each emotion value are used as features. The features extracted in this way are listed in Table 1. These features were selected from the studies[22–24] mentioned in Sect. 3.2.

The work attitude estimation model is constructed by collecting data beforehand and using machine learning for training. We use random forest, suitable for learning with many explanatory variables, for the estimation model.

4. Evaluation

In this section, we demonstrate the feasibility of the Work Attitude PLR collection platform by constructing and evaluating a work attitude estimation model using data collected via smartphones. We show the estimation performance based on data collected from a preliminary experiment conducted prior to a large-scale empirical study.

Table 1
List of features extracted from each channel of data collected by the smartphone.

Channel	Features	Description
Facial images	smile anger contempt disgust fear happiness neutral sadness surprise	0–1 Closer to 1 corresponds to the emotion The mean (*m*), median (*med*), variance (*v*), and maximum (*max*) of each emotion value are used as the feature values. For example, the mean of "smile" is "smile_m". From Face API (Microsoft)
Voice	calm anger joy sorrow energy	0–50 Closer to 50 corresponds to the emotion From Empath API (Empath)
Text	Pos (Positive) Neu (Neutral) Neg (Negative)	Mood of the text as a whole
	P (Positive) N (Negative) PN (Both P & N) sad anxious good excited happy relieved dislike	Counting the words of the corresponding emotion in the text From Cotoha API (NTT Communications)
GPS	Distance	Total distance traveled
Step	Step	Number of steps
Questionnaire	Sleep efficiency	Sleep efficiency

4.1 Collected data

Nine male students aged 23 to 24 participated in this experiment. The experiment lasted for two weeks, during which data were collected for 10 days, excluding holidays. The subjects were required to record videos both in the morning and evening while behaving as usual for the rest of the time. As a result, 78 morning and 77 evening samples were collected, totaling 155 samples.

To evaluate the estimation performance of work attitude, the ground truth values for work attitude were obtained through questionnaires conducted after each video recording.

This experiment was conducted after review and approval by the Ethics Review Committee of Nara Institute of Science and Technology (Approval No. 2019-I-14), and the subjects were informed of the details of the experiment and their consent was obtained in advance.

4.2 Work attitude estimation model

Two types of model were constructed for estimating work attitude: one utilizing all features and the other using selected features. Both models were evaluated using leave-one-out cross-validation, in which one sample was used as test data and the remaining samples from all subjects were used as training data. To estimate $RE1$–4 and $RS1$–3, which are related to how leisure time is spent, 78 samples taken in the morning before work were used, and to estimate $WE1$–4, which are related to how work time is spent, 77 samples taken in the evening after work were used. The estimation model was constructed using MATLAB.

Among the 57 features listed in Table 1, sleep efficiency was excluded when estimating $WE1$–4 as it is considered to only affect work engagement during subsequent work periods. Therefore, 56 features were used for estimating $WE1$–4, and all 57 features were used for estimating $RE1$–4 and $RS1$–3.

Feature selection was performed on the basis of Gini importance. Features were sequentially added starting from the highest importance, and the subset of features that resulted in the highest performance was adopted.

5. Results

In this section, we present the results of the evaluation experiment described in Sect. 4. First, we discuss the distribution of work attitude as reported by subjects through questionnaires. Then, we present the performance evaluation results of the work attitude estimation model. Performance evaluation was conducted using accuracy and $F1$ scores.

5.1 Questionnaire results

The ground truth values for work attitude reported by subjects through questionnaires posed challenges for evaluation due to the very few samples with a response of 0. To ensure a sufficient number of samples for each class, we consolidated the rating categories: 5-point and 7-point scales (for all scales except $RS3$) were consolidated into 3-point scales, and the 4-point scale ($RS3$) was consolidated into a 2-point scale. The results of this consolidation are shown in Fig. 3.

5.2 Estimation results

The accuracy of the work attitude estimation model for each scale is shown in Fig. 4. The average accuracies for recovery experience (RE), recovery status (RS), and work engagement (WE) with feature selection were 57.37% (± 8.53; standard deviation, same as below), 52.96% (± 10.49), and 45.89% (± 4.17), respectively. Without feature selection, these values were 57.05% (± 11.96), 52.14% (± 6.58), and 55.41% (± 9.57), respectively. The overall average accuracies for all scales were 52.48% (± 8.82) with feature selection and 55.08% (± 9.07) without feature selection.

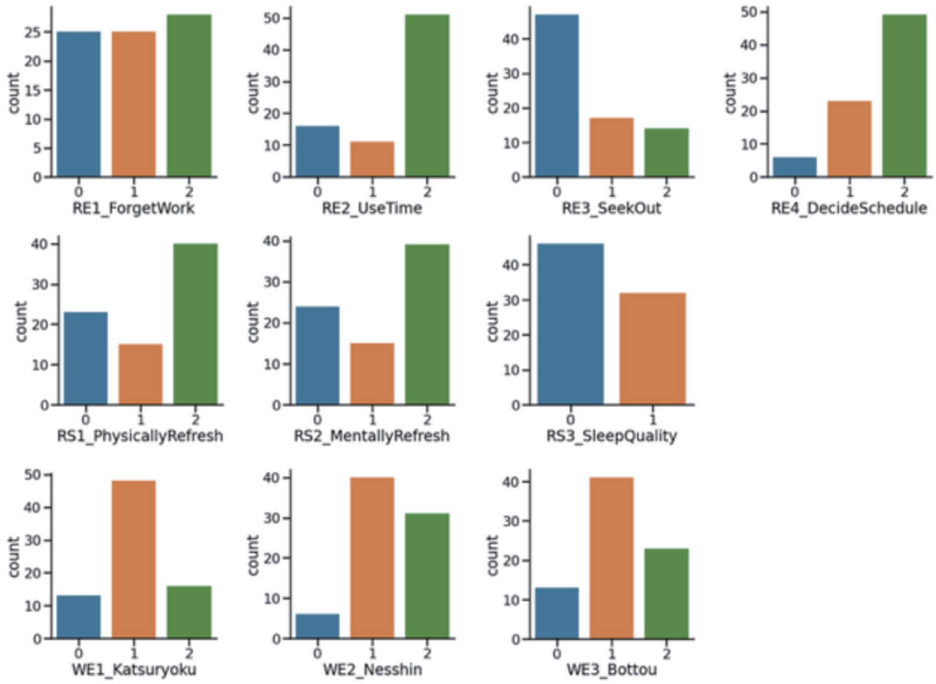

Fig. 3. (Color online) Postprocessing questionnaire results.

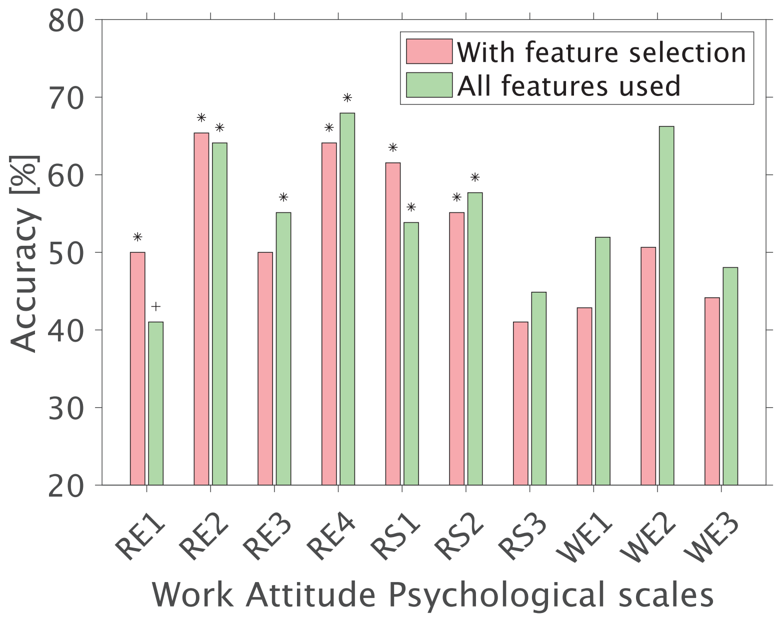

Fig. 4. (Color online) Accuracies of Work Attitude Estimation. The bar to the left of each scale shows the results with feature selection and the bar to the right shows the results without feature selection (permutation test, uncorrected, *: $P < 0.01$; +: $P < 0.05$).

The $F1$ scores of the work attitude estimation model for each scale are shown in Fig. 5. The average $F1$ scores for RE, RS, and WE with feature selection were 38.65% (± 12.73), 44.57% (± 9.74), and 29.12% (± 7.74), respectively. Without feature selection, these values were 36.70% (± 6.56), 39.58% (± 1.95), and 37.73% (± 7.01), respectively. The overall average $F1$ scores for all scales were 37.57% (± 11.36) with feature selection and 37.87% (± 5.26) without feature selection. Note that when feature selection was not performed, the $F1$ scores for $RE4$ and $WE2$ could not be calculated owing to the absence of classification cases for certain classes. The dashed bars show values where the $F1$ score was calculated by interpolating the corresponding precision as 0.

Next, we present the results of feature selection. The number of selected features for the estimation of each scale is shown in Fig. 6, and the frequency distribution of the selected features is shown in Fig. 7. The frequency distribution in the top row corresponds to $RE1$–4, the middle row to $RS1$–3, and the bottom row to $WE1$–3 estimations. Each horizontal axis shows the features listed in Table 1, and the vertical axis shows the frequency of selection during cross-validation.

6. Discussion

In the estimation of work attitude, both with and without feature selection conducted for three-class classification (two-class for $RS3$), an overall accuracy of around 50% was achieved. In particular, for $RE2$, $RE4$, and $RS1$–2, accuracy was significantly higher than the chance level, regardless of whether feature selection was performed or not. However, the $F1$ scores were approximately 37%, suggesting that the imbalance in the number of samples for each class biased the estimation results. This is also reflected in the fact that specific classes were entirely absent in the estimations of $RE4$ and $WE2$ without feature selection.

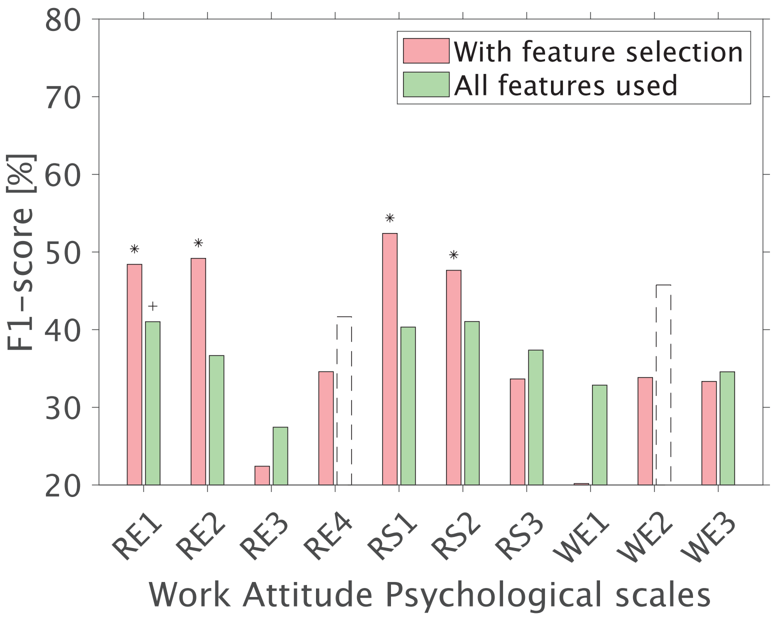

Fig. 5. (Color online) $F1$ scores of Work Attitude Estimatiovn. The bar to the left of each scale shows the results obtained with feature selection and the bar to the right shows the results obtained without feature selection (permutation test, uncorrected, *: $P < 0.01$; +: $P < 0.05$).

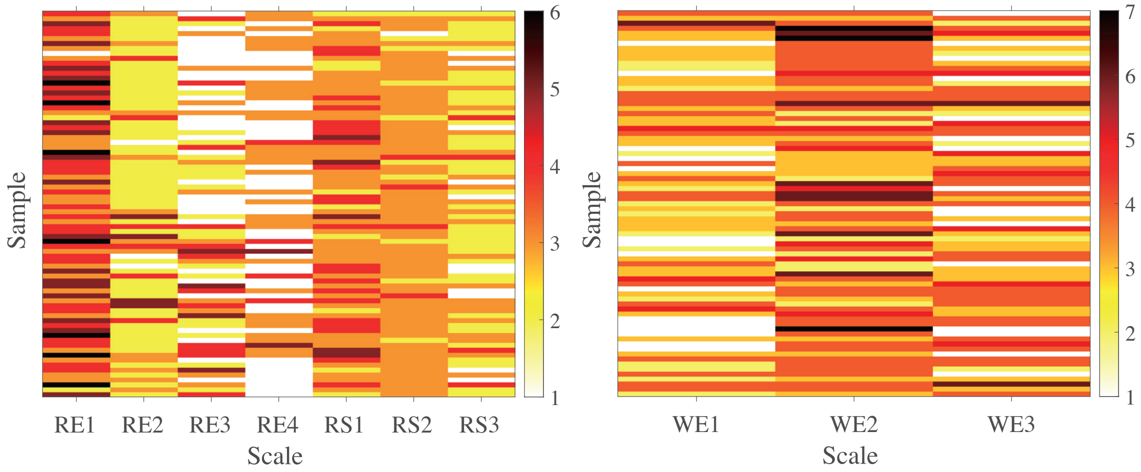

Fig. 6. (Color online) Number of selected features.

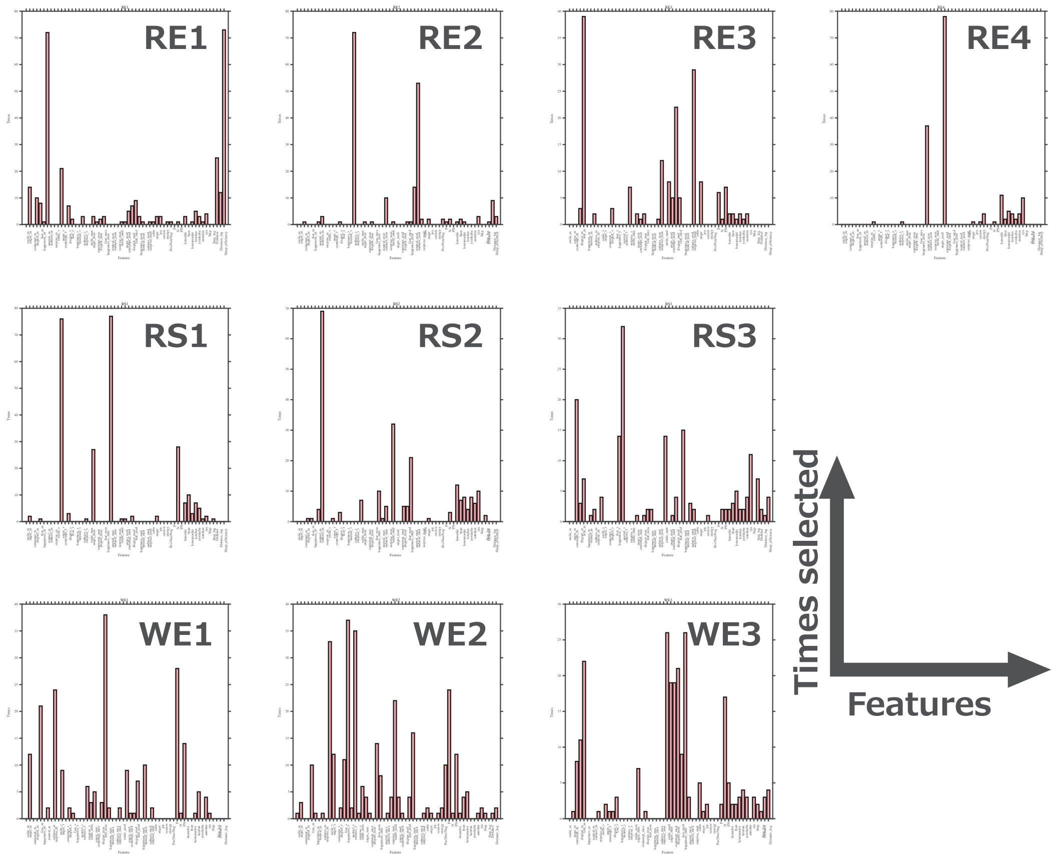

Fig. 7. (Color online) Distribution of number of times each feature was selected.

Comparing the scenarios with and without feature selection revealed no significant changes in overall accuracy and $F1$ scores. In terms of performance by scale, the performance shows that for $F1$ score, significance was shown for $RE2$ and $RS1$–2 only with feature selection, while for accuracy, significance was found for $RS3$ only without feature selection. However, for $RE1$, where the number of samples for each class was the most balanced, feature selection improved the estimation performance, achieving accuracy and $F1$ scores of around 50%, which were significantly higher than the chance level. From these observations, it can be inferred that collecting larger-scale data and balancing the sample sizes for each class may enable a more effective estimation for other scales as well.

The results of feature selection showed varying numbers of selected features and different frequency distributions of selected features across scales. This suggests that our proposed method, which utilizes multimodal information, is suitable for estimating work attitude. Ensuring a sufficient number of samples may clarify the relationship between each scale and its features, potentially reducing the data required for estimation.

In the case of $RE1$, which had the most substantial number of samples, a relatively large number of features were consistently selected in each estimation. Furthermore, in the frequency distribution of selected features, certain features (especially sleep efficiency and "neutral_m" in the facial images channel) were selected more frequently. However, similar trends were observed in the frequency distributions for other scales as well.

7. Conclusion

In this paper, we proposed the Work Attitude PLR collection platform, which enables the monitoring of workers' daily mental health. This platform estimates, accumulates, and provides feedback on work attitude by combining multiple existing psychological scales and using data obtainable from smartphones. Additionally, we highlighted the necessity of machine-learning-based estimation models to realize this platform and conducted experiments to evaluate the estimation performance and investigate the features used for estimation. These experiments were preliminary and conducted prior to a large-scale empirical study.

The experimental results showed that, for scales with a sufficient number of samples, feature selection improved estimation performance, achieving accuracy and $F1$ scores of approximately 50% in three-class classification, which was significantly higher than the chance level. For datasets with large sample imbalances, feature selection significantly improved the $F1$ score for some scales, but did not produce stable estimates of accuracy. Furthermore, the feature selection results indicated that the number and frequency distribution of selected features varied depending on the target scale, which indicate the effectiveness of using multimodal information in our method.

For future work, to achieve effective estimation, it is necessary to reduce sample imbalances. Therefore, we plan to conduct large-scale data collection experiments to ensure a sufficient number of samples. On the basis of this, we will implement empirical experiments using datasets processed with techniques such as downsampling to address imbalances. Additionally, we also plan to conduct a leave-one-user-out analysis to investigate the effect of user-specific trends on estimation performance. Furthermore, the experiment will require subjects of a wide range of ages and genders to test the generalizability of the estimated performance to any population.

In addition, in this work, we reduced the burden of daily monitoring by using only data acquired by smartphones, but recording videos every day is troublesome for users and may have a negative impact on continuity. To address this issue, we plan to investigate the estimation performance when reducing the necessary features for estimating work attitude, based on the relationships between each scale and feature indicated by the results. Additionally, we intend to examine the estimation performance by evaluating each data channel and their combinations to reduce the tasks imposed on the user.

Acknowledgments

This work was supported by MEXT "Innovation Platform for Society 5.0" Program Grant Number JPMX0518071489.

References

1 P. D. Harvey, B. R. Greenberg, and M. R. Serper: J. Clin. Psychol. **45** (1989) 786. https://doi.org/10.1002/1097-4679(198909)45:5<786::AID-JCLP2270450515>3.0.CO;2-P
2 Ministry of Health, Labour and Welfare of Japan: (in Japanese). https://www.mhlw.go.jp/content/000533925.pdf (accessed June 2024).
3 V. P. Cornet and R. J. Holden: J. Biomed. Inf. **77** (2018) 120. https://doi.org/10.1016/j.jbi.2017.12.008
4 C. Amenomori, T. Mizumoto, H. Suwa, Y. Arakawa, and K. Yasumoto: Wireless Mobile Communication and Healthcare, P. Perego, A. Rahmani, and N. TaheriNejad, Eds. (Springer, Cham, 2018) 91. https://doi.org/10.1007/978-3-319-98551-0_11
5 N. Jaques, S. Taylor, A. Azaria, A. Ghandeharioun, A. Sano, and R. Picard: 2015 Int. Conf. Affective Computing and Intelligent Interaction (IEEE, 2015) 222. https://doi.org/10.1109/ACII.2015.7344575
6 A. Sano, A. J. Phillips, A. Z. Yu, A. W. McHill, S. Taylor, N. Jaques, C. A. Czeisler, E. B. Klerman, and R. W. Picard: 2015 IEEE 12th Int. Conf. Wearable and Implantable Body Sensor Networks (IEEE, 2015) 1. https://doi.org/10.1109/BSN.2015.7299420
7 M. Boukhechba, A. R. Daros, K. Fua, P. I. Chow, B. A. Teachman, and L. E. Barnes: Smart Health **9–10** (2018) 192. https://doi.org/10.1016/j.smhl.2018.07.005
8 Y. Fukazawa, T. Ito, T. Okimura, Y. Yamashita, T. Maeda, and J. Ota: J. Biomed. Inf. **93** (2019) 103151. https://doi.org/10.1016/j.jbi.2019.103151
9 B. Bakker, J. J. Hakanen, E. Demerouti, and D. Xanthopoulou: J. Educ. Psychol. **99** (2007) 274. https://doi.org/10.1037/0022-0663.99.2.274
10 K. Suwabe, T. Maegawa, T. Mizumoto, H. Suwa, and K. Yasumoto: 2023 IEEE 12th Global Conf. Consumer Electronics (IEEE, 2023) 504. https://doi.org/10.1109/GCCE59613.2023.10315372
11 M. B. Morshed, K. Saha, R. Li, S. K. D'Mello, M. D. Choudhury, G. D. Abowd, and T. Plötz: Proc. ACM Interact. Mobile Wearable Ubiquitous Technol. 3 (ACM, 2019) Article 75. https://doi.org/10.1145/3351233
12 W. B. Schaufeli, T. W. Taris, and W. V. Rhenen: Appl. Psychol. **57** (2008) 173. https://doi.org/10.1111/j.1464-0597.2007.00285.x
13 C. Maslach and S. E. Jackson: Maslach Burnout Inventory (Consulting Psychologists Press, Palo Alto, 1986) 2nd ed., 20.
14 W. B. Schaufeli, M. Salanova, V. González-romá, and A. B. Bakker: J. Happiness Stud. **3** (2002) 71. https://doi.org/10.1023/A:1015630930326
15 W. B. Schaufeli and A. B. Bakker: J. Organiz. Behav. **25** (2004) 293. https://doi.org/10.1002/job.248
16 W. B. Schaufeli, A. Shimazu, J. Hakanen, M. Salanova, and H. D. Witte: Eur. J. Psychol. Assess. **35** (2019) 577. https://doi.org/10.1027/1015-5759/a000430
17 S. Sonnentag and C. Fritz: J. Occup. Health Psychol. **12** (2007) 204. https://doi.org/10.1037/1076-8998.12.3.204
18 A. Shimazu, S. Sonnentag, K. Kubota, and N. Kawakami: J. Occup. Health **54** (2012) 196. https://doi.org/10.1539/joh.11-0220-OA

19 C. Binnewies, S. Sonnentag, and E. J. Mojza: J. Organiz. Behav. **30** (2009) 67. https://doi.org/10.1002/job.541
20 D. J. Buysse, C. F. Reynolds, T. H. Monk, S. R. Berman, and D. J. Kupfer: Psychiatry Res. **28** (1989) 193. https://doi.org/10.1016/0165-1781(89)90047-4
21 S. Sonnentag, C. Binnewies, and E. J. Mojza: J. Appl. Psychol. **93** (2008) 674. https://doi.org/10.1037/0021-9010.93.3.674
22 Y. Fukazawa, N. Yamamoto, T. Hamatani, K. Ochiai, A. Uchiyama, and K. Ohta: J. Inf. Process. **28** (2020) 16. https://doi.org/10.2197/ipsjjip.28.16
23 F. Noroozi, M. Marjanovic, A. Njegus, S. Escalera, and G. Anbarjafari: IEEE Trans. Affective Comput. **10** (2019) 60. https://doi.org/10.1109/TAFFC.2017.2713783
24 A. A. Farhan, J. Lu, J. Bi, A. Russell, B. Wang, and A. Bamis: 2016 IEEE First Int. Conf. Connected Health: Applications, Systems and Engineering Technologies (IEEE, 2016) 264. https://doi.org/10.1109/CHASE.2016.27