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A Privacy-Preserving Sensor Approach to Analyze How Concentration Affects Desk Work Behavior

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Abstract: Remote work often leads to social isolation and reduced well-being for workers. To address this, we aim to share workers' concentration states to enhance their sense of connection without being monitored. However, most of the works overlook the privacy aspects of this issue. Therefore, this study proposes a privacy-preserving approach that uses keyboard and mouse logs, wrist and chair movement data, and a distance sensor to estimate concentration during desk work. To validate the privacy-preserving method to estimate concentration, we conduct controlled experiments under concentrated and unconcentrated conditions, with tasks classified by input intensity. Principal component analysis reveals that specific features of wrist and chair accelerometers are associated with concentration levels. These findings suggest that workers' concentration can be estimated without compromising privacy, providing a foundation for privacy-aware presence-sharing systems.

Keywords: Privacy-Preserving Sensing, Concentration Estimation, Desk Worker Analysis, Human Activity Recognition

1. INTRODUCTION

Remote work has become increasingly common in recent years. It is expected to reduce costs, improve the work-life balance of workers, and improve productivity and job satisfaction [1, 2], and its adoption is expected to continue to grow. On the other hand, remote workers are prone to experiencing feelings of loneliness, which is known to negatively impact mental health and well-being [2, 3].

To address this issue, several studies have explored sharing presence information among workers. Honda et al. [4] proposed a virtual office environment "Valentine" that measures the worker's concentration level and provides awareness accordingly. Ban et al. [5] found that being monitored in the workplace increased discomfort and motivation, whereas sharing work states decreased discomfort compared to the monitored condition. Some studies have utilized cameras and microphones to gather information on the presence of workers. While this approach provides valuable insights, it raises privacy concerns [6] and can undermine the trust between employees and their organizations. Additionally, Morrison-Smith et al. [7] suggested that using an ambient display to share work activities can motivate remote workers without disrupting their workflow. An ambient display is a system intended to convey information as if it were part of the environment, without demanding attention.

Therefore, our research aims to reduce isolation and improve well-being among remote workers by sharing work status and concentration levels with other remote workers using an ambient display while preserving their privacy and comfort. Ambient displays are often used to display ambiguous information, and we believe that privacy can be protected by using ambient displays. Furthermore, quantitatively measuring human concentration is challenging, as it is an ambiguous metric and can vary subjectively from person to person. Additionally, despite the diversity of tasks in desk work, workers often maintain similar postures with minimal body movements, which complicates their classification through machine learning techniques. To date, there has been no research that offers a privacy-aware approach for analyzing desk work behaviors.

To address this challenge, we propose a sensor-based method that utilizes keyboard and mouse logs, wrist and chair movement data, and a distance sensor. In this method, we use behavioral data using various non-intrusive sensors. Specifically, we examine the idle time of keyboard and mouse input, IMU (Inertial Measurement Unit) sensors, and a distance sensor. The IMU sensors on the chair and wrist are used to capture movement data, while the distance sensor is used to detect changes in upper body posture. To validate our sensor-based method, we performed controlled experiments under both concentrated and unconcentrated conditions and analyzed collected behavioral data with principal component analysis. Furthermore, we explore whether our methods for detecting concentration levels can align with privacy protection measures.

2. RELATED WORKS

In this section, we present the related works of privacy-aware human activity recognition, and estimating concentration levels.

Human Activity Recognition (HAR) using sensor technologies has become a well-established research field [6, 8-10]. With the advancement of HAR research, privacy risks have also increased [6]. Compared to vision-based activity recognition, sensor-based activity recognition offers the advantages of lower energy consumption [9] and fewer risks of private information leakage [6]. Furthermore, vision-based HAR can create a sense of surveillance and increase discomfort [5, 8], making sensor-based HAR more suitable for remote work envi-

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† Yuto Morioka is the presenter of this paper.

ronments from privacy and psychological perspectives.

Nishkam et al. [10] proposed a method for recognizing activities such as walking using a single accelerometer and machine learning. Activity recognition is formulated as a classification problem. Therefore, many studies use machine learning for activity recognition [6, 8, 10]. In addition, it is important to use the appropriate features to improve recognition accuracy of machine learning. However, desk workers perform diverse tasks while generally not making significant body movements. Consequently, activity classification using machine learning based on sensor data can be challenging. In sensor-based HAR, a technique called sensor fusion, which combines multiple sensor data, has been proven to improve recognition accuracy by compensating for insufficient features of a single sensor [9]. Although these sensors provide limited information individually, when combined, they are expected to detect differences in complex human behaviors.

Honda et al. [4] proposed "Valentine" system in which they estimate the concentration level of a worker by measuring the ratio of idle time in keyboard and mouse input and the frequency of chair movement. According to their findings, workers who concentrate rotate their chairs less frequently compared to those who are not concentrating, and the ratio of keyboard and mouse input idle time decreases during concentration. Their approach estimates concentration levels using keyboard and mouse input frequency and chair rotation frequency. However, since desk workers' behavior is small and complex, multimodal sensing is necessary to estimate concentration levels. Furthermore, their approach did not consider privacy and they shared workers' concentration information directly. To fill this gap, we propose sensor-based privacy-preserving method for sharing concentration levels.

3. PROPOSED DATA COLLECTION AND ANALYSIS METHOD

We propose a sensor-based method that utilizes keyboard and mouse input logs, wrist and chair movement data, and a distance sensor. In this proposal, we utilize a variety of sensors to measure the concentration of desk workers. The IMU sensors on the chair and wrists are used to extract movement data, and the distance sensor is used to detect changes in upper body posture.

3.1. Sensor Setup

To obtain behavior indicators, we used sensors to collect the data shown in Table 1. The placement of the sensor during the experiment is shown in Figure 1 and Figure 2. We used M5StickC Plus2 as the IMU attached to the wrist and backrest of the chair. M5StickC Plus2 is a microcontroller board with an integrated 6-axis IMU MPU6886 and communication functions. Figure 3 shows the directions of the axis of the IMU. For example, the x-axis acceleration of the chair's IMU sensor can detect rotational movements, while the y- and z-axis accelerations can detect movements that tilt the backrest.

Table 1 Sensor types and measurement targets

Sensor	Measured Data	Placement
IMU (MPU6886)	Wrist acceleration (x, y, z), Wrist angular velocity (x, y, z)	On wrist
IMU (MPU6886)	Chair acceleration (x, y, z), Chair angular velocity (x, y, z)	Chair backrest
Input monitor program	Key presses, mouse clicks, mouse movements, scrolls	PC
Ultrasonic distance sensor (HC-SR04)	Distance to worker	Below the monitor

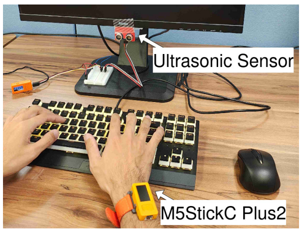

Fig. 1 Wrist sensor and distance sensor

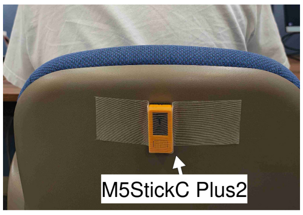

Fig. 2 Chair sensor

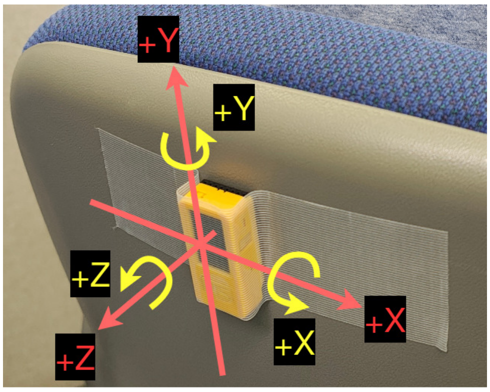

Fig. 3 Directions of acceleration (red) and angular velocity (yellow) corresponding to the x, y, and z axes

The sensor devices transmitted measurement data to the server through UDP communication. The IMU was sampled at 100 Hz and, to reduce noise, an average of 10 data points were recorded on the server. The ultrasonic sensor was attached 50 cm from the edge of the desk at the bottom of the monitor, measuring the distance to the worker every 300 ms and recording it on the server. The keyboard and mouse operation events were recorded on the server using a client program that monitored input.

3.2. Experimental Design and Procedure

We perform experiments with six Japanese university students, including three males and three females, under concentrated and unconcentrated conditions. All participants regularly use computers.

When measuring the behavior of desk workers using wearable sensors, differences in sensor data may arise between tasks that require intense input operations and those that do not. Therefore, to compare the behaviors of the desk workers, we prepared three tasks. The participants performed three tasks classified by intensity of the input activity and are shown in Table 2.

Table 2 Tasks categorized by activity intensity

Intensity	Task	Description
Low (use mouse)	Reading	Reading a Japanese story on a PC
Mid (use keyboard)	Typing	Typing and transcribing an English story on a PC
High (use mouse and keyboard)	Research	Searching the web and typing answers to a quiz

Each task was conducted under two conditions: concentrated and unconcentrated. In the concentrated condition, participants were instructed to "perform the task quickly and accurately." In the unconcentrated condition, a Japanese audio narration of the story was played, and participants were instructed to "focus on the content of the audio narration while performing the task." The trial order was counterbalanced. Each trial lasted 7 minutes. In total, data was collected from 36 trials (6 participants × 6 conditions). To reduce the effects of fatigue, a 7 minute break was given after the third trial. After each trial, participants rated their subjective concentration level on a 7-point Likert scale ranging from 1 (could not concentrate at all) to 7 (was very concentrated).

3.3. Data Preprocessing

We excluded the first 30 seconds after measurement began and the last 30 seconds before measurement ended, as these periods contained movements unrelated to the task. Additionally, we removed missing values from the IMU sensor data and values exceeding 400 cm from the distance sensor as outliers and applied linear interpolation to fill the gaps.

3.4. Feature Extraction

Figure 4 shows the changes in wrist IMU values during typing actions, and Figure 5 shows the changes in wrist IMU values during cup lifting actions. During cup lifting, the gyroscope values change with movement. In contrast, during typing actions, the gyroscope values show minimal changes. When we performed a principal component analysis that included the features of the wrist IMU gyroscope, we found that their contribution to the principal components was lower compared to other features. This suggests that wrist movements during keyboard and mouse operation involve little rotational motion. Therefore, we determined that the wrist IMU gyroscope sensor data would introduce noise and did not use it as a feature.

Following Nishkam et al. [10], we extracted the mean and standard deviation as features from the sensor data. We used a sliding-window approach for feature extraction from time series data. According to Banos et al. [11], a window size of 1-2 seconds provides a good trade-off between recognition speed and accuracy. Based on this, we set the window size to 2 seconds with a step size of 1 second. We calculated the mean and standard deviation of the wrist IMU accelerometer (acc)-x,y,z, chair IMU accelerometer-x,y,z, gyroscope (gyro)-x,y,z, and distance sensor data, resulting in 20-dimensional feature vectors. The features were standardized to have zero mean and unit variance to prevent bias due to scale differences.

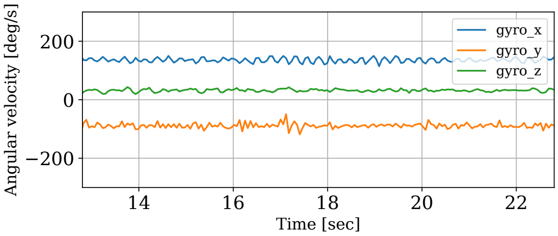

Fig. 4 Wrist gyroscope data during typing

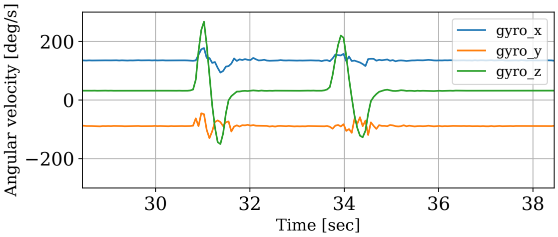

Fig. 5 Wrist gyroscope data during cup lifting

3.5. Principal Component Analysis

We examined the extracted features to understand the elements that influence differences in concentration levels. To identify the most important features, we performed the principal component analysis (PCA) on the data for each participant and task. The analysis procedure was as follows:

1. We performed dimensional reduction to 2D using PCA on features extracted from both concentrated and unconcentrated condition trials.
2. Statistical tests were performed on the reduced dimensions (PC1, PC2) to determine if there were significant differences between the concentrated and unconcentrated conditions.
3. We calculated Cohen's d as an effect size indicator to quantify the magnitude of differences.
4. For data with a Cohen's d absolute value of 0.8 or higher, we extracted the features with a high contribution (loading) to the principal components.

4. RESULTS

In this section, we present the results of our experiments and analyses.

4.1. Objective Indicators

First, we discuss the objective indicators. Figure 6 shows the difference in the ratio of idle time between unconcentrated and concentrated conditions for each partic-

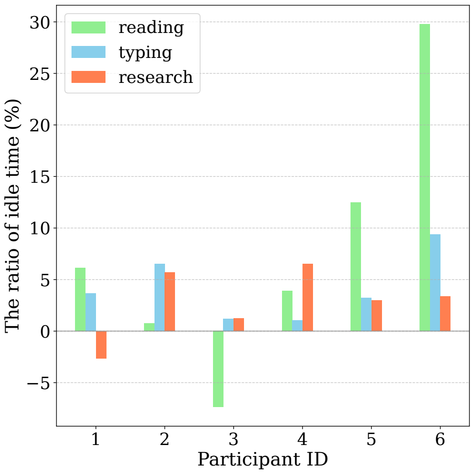

Fig. 6 The ratio of idle time for each task and participant (unconcentrated - concentrated)

ipant and task. Except for two data, the ratio of idle time was lower in the concentrated condition than in the unconcentrated condition. This is consistent with the results of previous research [4].

Figure 7 shows the difference in the number of characters typed in the typing task. Figure 8 shows the difference in the number of answers in the research task. For both tasks, except for two participants, the workload was higher in the concentrated condition than in the unconcentrated condition. For participants with reversed relationships, the trial order was concentrated followed by unconcentrated, suggesting that they became more efficient at the task due to familiarity.

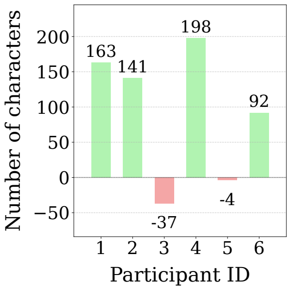

Fig. 7 Difference in the number of characters typed in the typing task (concentrated - unconcentrated)

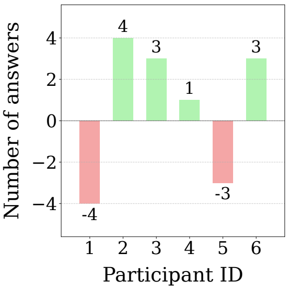

Fig. 8 Difference in the number of answers in the research task (concentrated - unconcentrated)

4.2. Subjective Indicators

In the subjective evaluation survey conducted after each trial, all participants reported higher subjective concentration levels in the concentrated condition compared to the unconcentrated condition. The mean difference in response was 3.67 ± 1.50.

4.3. PCA Results

Using PCA, we obtained the principal components, PC1 and PC2, for each participant and each task. However, some principal components did not show clear clustering. Therefore, we distinguished important components using Cohen's d as the effect size.

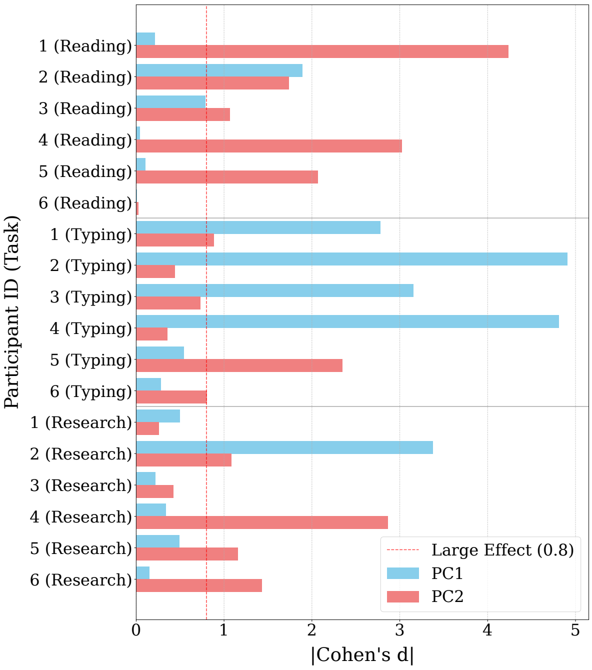

Fig. 9 Cohen's d (absolute values) for PC1 and PC2 by participant and task

Using the Shapiro-Wilk test, we determined that the data was not normally distributed. Therefore, we used the Wilcoxon signed-rank test to determine if there were significant differences in principal component scores between concentrated and unconcentrated conditions. The average sample size was 382.22. Figure 9 shows Cohen's d values for PC1 and PC2 for each participant and task.

Table 3 shows the explained variance ratio and the top three features with the highest contribution to the principal components for data with an absolute effect size value of 0.8 or higher. The test showed significant differences ($p < 0.0001$) for all principal components in Table 3.

5. DISCUSSION

In this section, we discuss the results and limitations of the experiment and, the possibility of Privacy-Aware Concentration Estimation.

5.1. Concentration vs. Unconcentration Indicators

From the results in Section 4.1 and 4.2, we can see that the subjective and objective indicators differ depending on the conditions. Therefore, we can conclude that this experiment successfully reproduced a situation in which the participant's concentration was low.

Next, we discuss the results of the sensor data analysis. Table 4 shows the features that appear five or more times in Table 3. We can observe that there is a bias in the features where differences appear. The mean values from the chair's acceleration sensor are particularly prevalent. However, the features of the distance sensor do not appear in Table 3, indicating their low contribu-

Table 3 PCA results for each participant and task (effect size ≥ 0.8)

Participant	Task	PC	Explained variance ratio	Effect size	Top features (loading)
1	Reading	PC2	0.20	4.24	wrist_acc_x_mean (0.45), chair_acc_y_mean (-0.43), chair_acc_z_mean (-0.43)
	Typing	PC1	0.25	-2.78	chair_acc_x_mean (0.37), chair_acc_y_mean (0.36), chair_acc_z_mean (0.36)
		PC2	0.17	-0.89	wrist_acc_x_mean (0.33), chair_gyro_y_std (0.32), chair_acc_z_std (0.32)
2	Reading	PC1	0.35	-1.89	wrist_acc_z_std (0.28), wrist_acc_x_std (0.26), wrist_acc_x_mean (-0.26)
		PC2	0.20	-1.74	chair_gyro_x_mean (0.32), wrist_acc_x_mean (-0.32), chair_acc_z_mean (-0.32)
	Typing	PC1	0.26	4.91	chair_acc_z_mean (0.40), chair_acc_y_mean (0.40), wrist_acc_y_mean (-0.38)
	Research	PC1	0.27	3.38	chair_acc_z_mean (0.37), chair_acc_y_mean (0.37), chair_acc_x_mean (0.37)
		PC2	0.25	1.08	wrist_acc_z_std (0.36), wrist_acc_x_std (0.35), wrist_acc_y_std (0.35)
3	Reading	PC2	0.17	-1.07	wrist_acc_x_mean (0.50), chair_acc_x_mean (-0.41), chair_acc_z_mean (-0.35)
	Typing	PC1	0.25	3.16	chair_acc_y_mean (0.41), chair_acc_z_mean (0.40), chair_gyro_y_mean (-0.38)
4	Reading	PC2	0.16	-3.02	chair_acc_z_mean (0.46), chair_acc_x_mean (-0.45), chair_acc_y_mean (0.44)
	Typing	PC1	0.30	4.81	chair_acc_z_mean (0.38), chair_acc_y_mean (0.38), chair_acc_x_mean (-0.37)
	Research	PC2	0.16	-2.86	chair_acc_z_mean (0.46), chair_acc_y_mean (0.45), wrist_acc_y_mean (0.38)
5	Reading	PC2	0.22	2.07	wrist_acc_x_mean (0.44), chair_acc_y_mean (-0.42), chair_acc_z_mean (-0.42)
	Typing	PC2	0.18	-2.35	chair_acc_z_mean (0.42), chair_acc_y_mean (0.41), chair_acc_x_mean (-0.41)
	Research	PC2	0.16	-1.16	chair_gyro_x_mean (0.45), chair_acc_y_mean (0.32), chair_acc_z_mean (0.32)
6	Typing	PC2	0.16	0.81	chair_gyro_y_std (0.34), chair_gyro_y_mean (0.33), chair_gyro_z_mean (-0.32)
	Research	PC2	0.15	1.43	chair_acc_z_mean (0.35), chair_acc_y_mean (0.35), chair_gyro_z_mean (0.31)

tion to the principal components. The chair_acc_x_mean represents the rotational movement of the chair, while the chair_acc_y_mean and chair_acc_z_mean are considered to represent changes in the angle of the backrest. The wrist_acc_x_mean represent the movement of the right hand between the keyboard and mouse, as well as the action of reaching keys located away from the home position, such as arrow keys and delete key. The differences in these features indicate that there are behavioral differences between high and low concentration states. In addition, these movements were shown to be detectable by the sensors used in this study.

Table 4 Feature frequency in Table 3 and detected behavior

Feature	Count	Detected Behavior
chair_acc_z_mean	14	Using the backrest
chair_acc_y_mean	12	Using the backrest
chair_acc_x_mean	6	Rotating the chair
wrist_acc_x_mean	6	Mouse-keyboard hand movements

Furthermore, the mean features appear more frequently than the std features. This is likely because desk work involves small movements and fewer repetitions, making the standard deviation less effective as a feature representing the variability of sensor values. Therefore, it is important to use mean features to capture changes in posture when sensing movements that do not change much.

However, although certain features appear more frequently, the specific features where differences appear vary depending on the individual and the task. Next, we focus on individuals and discuss differences in chair and wrist movements based on features.

5.1.1. Chair Movement

From the fact that all participants exhibit the features chair_acc_y_mean and chair_acc_z_mean, it can be inferred that there are differences in the movement of reclining the backrest between conditions. Additionally, except for Participant 6, all participants exhibit the feature chair_acc_x_mean, suggesting that these participants have differences in the rotational movement of the chair between conditions. Video recordings confirm a tendency for participants to recline the backrest and rotate the chair more frequently during unconcentrated conditions. In other words, there is a general tendency for increased chair movement during unconcentrated conditions across all participants.

5.1.2. Wrist Movement

participants 1, 2, 3, and 5 exhibit the feature wrist_acc_x_mean, suggesting differences in horizontal wrist movements between conditions. Furthermore, participants 2 and 4 exhibit the feature wrist_acc_y_mean, suggesting differences in vertical movements between conditions. Data from the wrist IMU and video recordings confirm a tendency for faster and more frequent wrist movements during concentrated conditions. In other words, some participants exhibit more active hand movements during concentrated conditions.

5.2. Limitations

In this experiment, the gyroscope data from the IMU had a low contribution to the principal components. This is likely because the acceleration sensor detects gravitational acceleration and captures changes in posture as features, whereas the gyroscope captures instantaneous rotations, making it less effective for sensing actions with little movement, such as desk work. Therefore, when using gyroscope data as features for desk work actions, it is necessary to integrate the measured data and utilize it as posture information.

In addition, this experiment involved only six participants, all students. Thus, the findings are insufficient to represent the general tendencies of desk workers. Future studies should increase the number of participants and focus on desk workers performing tasks as company employees.

5.3. Privacy-Aware Concentration Estimation

Based on the experimental results, we discuss the possibility of balancing privacy protection and concentration estimation. The features that show differences between concentrated and unconcentrated conditions vary depending on the individual and the task. However, features commonly observed in many individuals were also identified. In addition, concentration is an ambiguous indicator and individual differences are significant. For example, even if workers exhibit the same movements, their subjective concentration levels may not necessarily be the same. Therefore, by deliberately defining concentration broadly and exhibit using ambient display, it is possible to absorb the effects of individual differences.

Using the sensors employed in this study, we consider whether a rough estimate of desk workers' concentration levels is possible. First, the wrist and chair IMU sensors provide information about workers' posture and movements. Although the distance sensor had a low contribution, it is sufficient to detect whether a worker is seated. Furthermore, by analyzing keyboard and mouse input, as well as idle time, it is possible to estimate concentration levels. From these observations, we conclude that the sensors used in this study can estimate the concentration levels of desk workers while protecting privacy.

6. CONCLUSION

In this study, we proposed a privacy-preserving sensor approach to estimate the concentration levels of desk workers. We analyzed the behavior of desk workers using multiple sensors to investigate which metrics show differences between concentration and unconcentration states. The results revealed that although there are individual differences in behavior between concentration and unconcentration states, during unconcentration periods, the frequency of posture changes increases, and hand movements decreased. Additionally, the findings suggest that focusing on chair and wrist movement may enable the estimation of a desk worker's concentrated unconcentrated state using only privacy-preserving sensors.

In the future, we plan to conduct a data analysis incorporating physiological data such as heart rate and GSR (Galvanic Skin Response) to assess concentration levels for individuals whose behavior does not reflect their concentration level. Based on sensor analysis results, we will implement a system that estimates the concentration levels from sensor data and naturally shares the concentration level of remote workers using an ambient display.

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