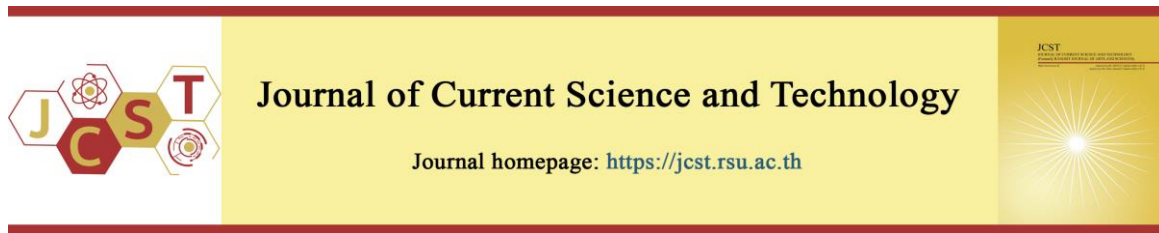


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Real-Time Stress Profiling in University Students During Post-COVID-19 Recovery and PM_{2.5} Exposure Using a Web Application

Pongjan Yoopat^{1,*}, Karn Yongsiriwit², Thannob Aribarg², Nisakorn Julraksa¹, and Weerawat Liammanee¹

¹Ergonomics Unit, Department of Medical Science, Faculty of Science, Rangsit University, Pathum Thani 12000, Thailand

²College of Digital Innovation Technology, Rangsit University, Pathum Thani 12000, Thailand

*Corresponding author; E-mail: pongjan.y@rsu.ac.th

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Abstract

This study compared stress profiles of Thai university students during post-COVID-19 recovery (2024) and peak PM_{2.5} exposure (2025) using the Find My Stress Progressive Web Application (PWA). A cross-sectional design enrolled 613 students (post-COVID-19: $n = 303$; PM_{2.5}: $n = 310$). Participants completed PWA-based assessments including demographic profiling, task-related stressor ratings (0–10 scale), Subjective Workload Index (SWI) computation, and activity-based evaluations across four daily domains. Handgrip strength normalized by BMI (HG/BMI) was measured in the PM_{2.5} cohort. Usability was assessed via a 14-item questionnaire ($n = 372$). Data were analyzed using independent-samples t -tests, Pearson correlations, and stepwise regression ($p < .05$). The post-COVID-19 cohort exhibited significantly higher SWI ($M = 3.09$, $SD = 0.85$) than the PM_{2.5} cohort ($M = 2.37$, $SD = 0.99$; $p < .001$, Cohen's $d = 0.78$), reflecting elevated psychosocial strain. The PM_{2.5} cohort reported greater environmental discomfort (air quality, dust, illumination) and biomechanical burden (adverse posture, restricted movement). Stepwise regression identified six predictors of HG/BMI: time, noise, dust, vibration, organizational factors, and gender ($r = 0.674$, $p < .001$). SWI correlated positively with fatigue and task complexity and negatively with motivation and autonomy. The PWA demonstrated excellent reliability (Cronbach's $\alpha = 0.957$). The Find My Stress PWA effectively captured context-specific stress patterns: elevated psychosocial workload during post-pandemic recovery and heightened environmental strain under PM_{2.5} exposure. These findings support the integration of scalable digital ergonomics tools into university health systems for real-time stress monitoring.

Keywords: *progressive web application; digital stress monitoring; Subjective workload index; university students; PM_{2.5} air pollution; post-pandemic stress; environmental stressors; ergonomic assessment; physical performance*

1. Introduction

University students worldwide face escalating stress levels driven by increasing academic demands, developmental transitions, and socioeconomic pressures, with significant consequences for mental health and academic performance (Campbell et al., 2022; Murakami et al., 2025; Zhang, 2020). These challenges have been markedly amplified in recent years as students have confronted successive crises, including the COVID-19 pandemic (Sutthigoon et al., 2025) and severe environmental events such as Thailand's recurring PM_{2.5} pollution episodes (Bran et al., 2024).

These events have underscored a critical need for scalable, real-time stress monitoring instruments capable of adapting to diverse learning and living conditions.

In response to this need, the Find My Stress Progressive Web Application (PWA) was developed as a digital health tool for real-time assessment of psychosocial, ergonomic, and environmental stressors. The PWA enables users to evaluate task-related stress across common academic and lifestyle activities including studying, completing assignments, using social media, and performing household chores

using a validated Subjective Workload Index (SWI) framework (Yoopat et al., 2024). The system generates immediate, personalized feedback based on task load, duration, and perceived discomfort, enabling users to identify stress hotspots and receive actionable recommendations for risk mitigation.

Although a substantial body of literature has documented the adverse psychological effects of the COVID-19 pandemic on university students including heightened anxiety, depression, and academic disengagement (Alibudbud, 2021; Chutipattana et al., 2022; Shafiq et al., 2021) and a separate line of research has established the cognitive and physiological consequences of PM_{2.5} exposure (Faherty et al., 2025; Ke et al., 2022), these two domains have been investigated largely in isolation. Studies examining pandemic-related stress have predominantly relied on retrospective self-report surveys without capturing real-time, activity-specific workload variation (Mungkhunthod et al., 2026), while research on air pollution and health has focused primarily on respiratory, cardiovascular, or neurocognitive endpoints, with limited attention to ergonomic and biomechanical dimensions of daily functioning. Critically, no study to date has directly compared how these two qualitatively distinct crises—one primarily psychosocial, the other predominantly environmental—differentially shape students' perceived workload, physical discomfort, and functional capacity across routine daily activities. Furthermore, existing stress assessment tools in university settings are typically domain-specific, assessing either psychological well-being or environmental exposure but rarely within an integrated, scalable digital framework.

This study addresses these gaps by employing the Find My Stress Progressive Web Application (PWA) to simultaneously profile psychosocial, ergonomic, and environmental stressors among Thai university students across two crisis periods post-COVID-19 recovery (2024) and peak PM_{2.5} exposure (2025). The study was guided by two research questions: (1) To what extent can the Find My Stress PWA effectively monitor students' stress in real time across daily activities? (2) How do users perceive its usability and potential for broader implementation in digital health contexts?

1.1 Background: Post-Pandemic and Environmental Stressors

The COVID-19 pandemic disrupted academic schedules, social connections, and mental health on a

global scale, with consequences persisting well into the recovery period (Noiprasert et al., 2024). Research consistently demonstrates that university students experienced heightened anxiety, depression, and difficulties with academic reintegration, driven by social isolation, disrupted interpersonal relationships, and fear of contagion (Alibudbud, 2021; Chutipattana et al., 2022; Malolos et al., 2021; Shafiq et al., 2021). These psychosocial challenges have continued to shape the post-pandemic academic experience.

Concurrently, Thailand's PM_{2.5} burden typically peaks during the dry-season months of January through April, driven by biomass burning and stagnant meteorological conditions. Multiple datasets document elevated fine particulate and black carbon fractions during this period, with frequent exceedances of national air quality standards in Bangkok and northern regions (Bran et al., 2024). Beyond established respiratory and cardiometabolic risks, acute PM_{2.5} exposure has been shown to impair cognition within hours: Faherty et al. (2025) reported significant decrements in selective attention and emotion recognition following brief PM_{2.5} exposure compared to clean air, directly supporting the inclusion of cognitive load-related SWI components in the present study.

Furthermore, emerging population-level and mechanistic studies link PM_{2.5} exposure to musculoskeletal and ergonomic strain through pathways including elevated risks of musculoskeletal diseases, skeletal muscle mitochondrial dysfunction, and systemic inflammation (Cheng et al., 2024; Ding et al., 2025). These biological mechanisms plausibly amplify perceived workload, fatigue, and discomfort during routine tasks. Taken together, these findings justify the comparison of post-COVID-19 (2024) and peak PM_{2.5} (2025) contexts and motivate the present study's objectives.

2. Objectives

This study aimed to: (1) compare stress profiles of Thai university students during post-COVID-19 recovery (2024) and peak PM_{2.5} exposure (2025); (2) assess perceived workload, environmental discomfort, and physical performance (handgrip strength) across daily activity domains; (3) examine correlations among workload, fatigue, task complexity, and environmental factors; and (4) evaluate the usability of the Find My Stress Progressive Web Application as a multidimensional stress assessment tool.

3. Methods

3.1 Study Design

A cross-sectional study was conducted at a private university near Bangkok, Thailand, during February and March of 2024 and 2025. The study employed the Subjective Workload Index (SWI), task-related discomfort evaluations, and handgrip strength measurements to characterize stress responses across two distinct environmental contexts. Data collection was performed using the Find My Stress Progressive Web Application (PWA) (Yoopat et al., 2024), which had demonstrated excellent internal consistency (Cronbach's $\alpha = 0.918$) in previous validation studies.

3.2 Ethical Considerations

This study was conducted in accordance with the Declaration of Helsinki. The protocol was approved by the Ethical Review Board of Rangsit University (Approval No. ERB2024-109, dated July 1, 2024). All participants received comprehensive information regarding study objectives, procedures, and data handling, and provided written informed consent prior to participation. Participant anonymity and data confidentiality were maintained throughout, with all personal identifiers removed during analysis.

3.3 Participants

A purposive sample of 613 full-time university students (aged 17–25 years) was recruited through digital outreach channels, including social media announcements and university communication platforms. Eligible participants were full-time students (Thai and international) with a minimum of one year of academic experience at the institution. Students were excluded if they exceeded 25 years of age, provided incomplete baseline demographic data, or failed to complete the application-based assessment. The final sample comprised 303 students in the post-COVID-19 cohort (February–March 2024) and 310 students in the PM_{2.5} exposure cohort (February–March 2025).

3.4 Data Collection Procedures and Instruments

Data were collected using the Find My Stress PWA, a validated browser-based platform for multidimensional stress assessment (Yoopat et al., 2024). Participants accessed the application via Chrome or Edge browsers on personal devices and completed a standardized five-stage assessment protocol.

Following authentication via Gmail credentials, participants entered demographic information including

age, sex, weight, height, and academic department. They then completed a structured evaluation of eight task-related stressors using a 0–10 Likert scale. Six negative stressors were assessed: central fatigue, peripheral fatigue, risk perception, concentration demands, task complexity, workload rhythm, and responsibility. Two positive factors, intrinsic task motivation and autonomy, were also evaluated. The Subjective Workload Index was computed as:

$$SWI = \frac{[(\text{sum of negative factors}) - (\text{sum of positive factors})]}{8}$$

Participants with SWI scores ≥ 2 completed a detailed task-specific analysis across four daily activity domains: academic study, assignment completion, social media usage, and household chores. For each activity, participants rated environmental discomfort factors (illumination, noise, air quality, dust, heat, vibration) and biomechanical factors (posture, movement restrictions, organizational demands) on a 0–5 scale, along with time allocated to each activity.

Physical performance was assessed in the PM_{2.5} cohort using handgrip strength as a proxy indicator of functional capacity. Measurements were obtained with a calibrated T.K.K.5401 Grip-D digital hand dynamometer (Takei Scientific Instruments Co., Ltd., Tokyo, Japan). Each participant performed two maximal voluntary contractions per hand in a standing position with the arm fully extended. The highest value per hand was recorded, and values were normalized by body mass index (HG/BMI ratio) and classified according to Thai national fitness standards (Department of Physical Education, 2019).

Application usability was evaluated by 372 participants immediately following completion of the stress assessment. A 14-item questionnaire assessed perceived usability across multiple dimensions including cross-device compatibility, ease of installation, interface design quality, content accuracy, font readability, and relevance of system-generated recommendations using a 5-point Likert scale (1 = strongly disagree; 5 = strongly agree).

3.5 Statistical Analysis

All analyses were performed using IBM SPSS Statistics version 21.0 (IBM Corp., Armonk, NY, USA). Descriptive statistics (means, standard deviations, frequencies, and percentages) summarized participant demographics and stressor ratings. Data distributions were examined using Shapiro–Wilk tests and Q–Q plots; homogeneity of variances was evaluated using Levene's test. Where parametric assumptions were violated,

Welch’s adjusted *t*-test was employed, supplemented by non-parametric Mann–Whitney *U* sensitivity analyses. Independent-samples *t*-tests compared SWI scores, workload factors, and environmental discomfort ratings between cohorts. Effect sizes were quantified using Cohen’s *d* with 95% confidence intervals. Pearson correlation coefficients examined bivariate associations between SWI and psychosocial, environmental, and biomechanical stressors. Multivariable linear regression (stepwise selection) identified significant predictors of HG/BMI ratio, with model diagnostics including variance inflation factors, residual normality, and homoscedasticity assessment. Internal consistency of the usability questionnaire was evaluated using Cronbach’s alpha. Statistical significance was set at a two-tailed $\alpha = .05$.

4. Results

4.1 Demographic Characteristics and Baseline Comparisons

The demographic characteristics of the two cohorts are summarized in Table 1. The post-COVID-

19 and PM_{2.5} groups were broadly comparable in age, weight, height, and body mass index. Sex distribution did not differ significantly between groups. Although small numerical differences were observed in age and BMI, the 95% confidence intervals of mean differences and negligible effect sizes (Cohen’s *d* approaching zero) indicated that these differences lacked practical significance. Accordingly, demographic characteristics are unlikely to confound the observed differences in stress profiles between cohorts.

4.2 Perceived Workload and Psychosocial Stressors

Comparisons of workload characteristics between cohorts are presented in Table 2. The post-COVID-19 group exhibited significantly higher overall subjective workload, as reflected by elevated SWI scores ($M = 3.09$, $SD = 0.85$ vs. $M = 2.37$, $SD = 0.99$; mean difference = 0.72, 95% CI [0.58, 0.87], $t(611) = 9.68$, $p < .001$). This difference corresponded to a moderate-to-large effect (Cohen’s *d* = 0.78, 95% CI [0.62, 0.94]), indicating substantial practical significance.

Table 1 Demographic characteristics of university students in the post-COVID-19 and PM_{2.5} cohorts (M ± SD)

Variable	Post-COVID-19 (M ± SD)	PM _{2.5} (M ± SD)	Mean Difference (95% CI)	<i>t</i>	<i>p</i> -value	Cohen’s <i>d</i> (95% CI)
Age (yr)	20.50 ± 1.48	20.66 ± 1.68	−0.41, 0.09	−1.251	0.212	−0.10 [−0.26, 0.06]
Weight (kg)	59.00 ± 13.00	60.00 ± 17.00	−3.13, 1.66	0.602	0.547	−0.07 [−0.22, 0.09]
Height (cm)	164.00 ± 8.00	164.00 ± 9.00	−0.42, 2.15	1.323	0.186	0.00 [−0.16, 0.16]
BMI (kg/m ²)	22.00 ± 4.00	22.00 ± 6.00	−1.33, 0.26	−1.318	0.189	0.00 [−0.16, 0.16]

Note: M = mean; SD = standard deviation; CI = confidence interval. Group comparisons were conducted using independent-samples *t*-tests. Cohen’s *d* is reported with 95% confidence intervals. Statistical significance was set at $p < .05$ (two-tailed).

Table 2 Perceived workload factors and Subjective Workload Index (M ± SD)

Variable	Post-COVID-19 (M ± SD)	PM _{2.5} (M ± SD)	Mean Difference (95% CI)	<i>t</i>	<i>p</i> -value	Cohen’s <i>d</i> (95% CI)
Fatigue	6.56 ± 2.85	5.53 ± 2.13	0.63, 1.43	5.071	<0.001	0.41 [0.25, 0.57]
Risk	4.52 ± 1.19	3.63 ± 2.15	0.57, 1.23	5.334	<0.001	0.51 [0.35, 0.67]
Concentration	6.10 ± 1.69	5.36 ± 2.21	0.43, 1.05	4.658	<0.001	0.38 [0.22, 0.54]
Complexity	6.31 ± 1.65	5.53 ± 2.12	0.48, 1.08	5.093	<0.001	0.41 [0.25, 0.57]
Work rhythm	5.61 ± 1.62	4.97 ± 1.93	0.35, 0.92	4.414	<0.001	0.36 [0.20, 0.52]
Responsibility	6.74 ± 1.81	6.37 ± 2.48	0.16, 0.71	2.057	0.041	0.17 [0.01, 0.33]
Job interest	5.68 ± 2.03	6.37 ± 2.16	−1.03, −0.36	−4.100	<0.001	−0.33 [−0.49, −0.17]
Autonomy	5.45 ± 2.01	6.00 ± 2.38	−0.95, −0.25	−3.348	0.001	−0.25 [−0.41, −0.09]
SWI	3.09 ± 0.85	2.37 ± 0.99	0.58, 0.87	9.676	<0.001	0.78 [0.61, 0.94]

Note: Note. M = mean; SD = standard deviation; CI = confidence interval; SWI = Subjective Workload Index. Workload factors were rated on a 0–10 scale. Job interest and autonomy are positive factors; all remaining variables are negative stressors. Group comparisons were conducted using independent-samples *t*-tests. Cohen’s *d* is reported with 95% confidence intervals. Statistical significance was set at $p < .05$ (two-tailed).

Table 3 Perceived environmental, organizational, and biomechanical workload factors during study, assignment, social media, and household chore tasks (M ± SD)

Variable	Post-COVID (M ± SD)	PM _{2.5} (M ± SD)	Mean Difference (95% CI)	<i>t</i>	<i>p</i> -value	Cohen's <i>d</i> (95% CI)
Study						
Heat (A)	2.37 ± 1.43	2.63 ± 1.40	-.5365, .0071	-1.913	0.056	-0.18 [-0.34, -0.03]
Noise	2.65 ± 1.36	2.44 ± 1.30	-.0474, .4640	1.601	0.110	0.16 [-0.02, 0.36]
Vibration	1.75 ± 1.30	1.53 ± 1.17	-.0168, .4493	1.824	0.069	0.18 [0.02, 0.34]
Air quality	1.78 ± 1.27	2.77 ± 1.35	-1.2450, -.7466	-7.853	<0.001	-0.76 [-0.92, -0.59]
Light	1.76 ± 1.19	2.77 ± 1.34	-1.2543, -.7784	-8.394	0.000	-0.81 [-0.97, -0.64]
Dust	2.19 ± 1.44	3.36 ± 1.49	-1.4524, -.89414	-8.211	0.041	-0.80 [-0.96, -0.63]
Organization	1.71 ± 1.16	2.59 ± 1.95	-1.0991, -.6677	-8.049	<0.001	-0.55 [-0.71, -0.39]
Movement	2.26 ± 1.86	2.58 ± 1.26	.6320, -.0073	-2.012	0.045	-0.20 [-0.36, -0.04]
Posture	2.02 ± 1.16	2.78 ± 1.08	-.9794, -.5448	-6.892	<0.001	-0.68 [-0.84, -0.52]
Assignment						
Heat (B)	2.35 ± 1.37	2.30 ± 1.30	-.2081, .3138	0.398	0.691	0.04 [-0.12, 0.20]
Noise	2.27 ± 1.34	2.03 ± 1.34	.0281, .4921	1.753	0.080	0.18 [0.02, 0.34]
Vibration	1.72 ± 1.38	1.44 ± 1.22	.0337, .5269	2.235	0.026	0.21 [0.01, 0.41]
Air quality	1.83 ± 1.29	2.41 ± 1.41	-.8392, -.3235	-4.431	0.001	-0.43 [-0.59, -0.27]
Light	1.85 ± 1.20	2.54 ± 1.41	-.9374, -.4452	-5.520	0.000	-0.54 [-0.74, -0.34]
Dust	1.94 ± 1.40	2.65 ± 1.67	-1.0129, -.3975	-4.512	0.000	-0.46 [-0.66, -0.26]
Organization	1.63 ± 1.29	2.29 ± 1.26	-.9073, -.4142	-5.233	0.00	-0.09 [-0.29, -0.11]
Movement	2.10 ± 1.14	2.41 ± 1.34	-.5555, -.0588	-2.435	0.016	-0.25 [-0.41, -0.09]
Posture	2.01 ± 1.14	2.62 ± 1.16	-.8373, -.3934	-5.449	0.000	-0.53 [-0.69, -0.37]
Social media						
Heat (C)	2.17 ± 1.39	1.88 ± 1.34	.0234, .5536	2.139	0.033	0.21 [0.01, 0.41]
Noise	2.21 ± 1.36	1.99 ± 1.19	-.0184, .4576	1.765	0.078	0.17 [-0.03, 0.37]
Vibration	1.55 ± 1.29	1.57 ± 1.27	-.2674, .2294	-0.150	0.881	-0.02 [-0.17, 0.14]
Air quality	1.65 ± 1.24	2.21 ± 1.48	-.8347, -.2929	-4.098	0.000	-0.42 [-0.70, -0.30]
Light	1.86 ± 1.22	2.50 ± 1.38	-.8890, -.3780	-4.880	0.000	-0.50 [-0.65, -0.33]
Dust	1.81 ± 1.40	2.20 ± 1.64	-.6926, -.0899	-2.556	0.011	-0.26 [-0.46, -0.06]
Organization	1.37 ± 1.22	2.04 ± 1.34	-.9211, -.4337	-5.462	0.000	-0.53 [-0.73, -0.33]
Movement	1.97 ± 1.22	2.27 ± 1.29	-.5416, -.0611	-2.465	0.014	-0.24 [-0.50, -0.06]
Posture	1.75 ± 1.17	2.47 ± 1.14	-.9407, -.4940	-6.312	0.000	0.62 [-0.82, -0.42]
House chores						
Heat (D)	2.68 ± 1.38	2.30 ± 1.31	.1139, .6385	2.819	0.005	0.28 [-0.08, -0.48]
Noise	2.00 ± 1.36	2.04 ± 1.35	-.3021, .2229	-0.297	0.767	-0.03 [-0.23, 0.17]
Vibration	1.64 ± 1.32	1.44 ± 1.22	-.0568, .4407	1.516	0.130	0.16 [-0.04, 0.36]
Light	1.64 ± 1.28	2.54 ± 1.41	-1.1573, -.6461	-6.933	0.000	-0.68 [-0.88, -0.48]
Air quality	2.01 ± 1.36	2.41 ± 1.41	-.6654, -.13406	-2.957	0.767	-0.29 [-0.49, -0.09]
Dust	2.52 ± 1.41	2.65 ± 1.68	-.4430, .1726	-0.865	0.388	0.09 [-0.29, 0.11]
Organization	1.55 ± 1.32	2.20 ± 1.26	-1.0043, -.5506	-5.871	0.000	-0.58 [-0.78, -0.38]
Movement	2.11 ± 1.17	2.41 ± 1.34	-.4079, .0814	-0.314	0.190	-0.24 [-0.44, -0.04]
Posture	2.01 ± 1.16	2.63 ± 1.16	-.7626, -.3103	-4.701	0.000	-0.54 [-0.74, -0.34]

Note. M = mean; SD = standard deviation; CI = confidence interval. Environmental and biomechanical discomfort factors were rated on a 0–5 scale across four daily activity domains: Study, Assignment, Social media, and House chores. Effect sizes are reported as Cohen's *d*. Group comparisons were conducted using independent-samples *t*-tests. Statistical significance was set at $p < .05$ (two-tailed). Full data are provided in the supplementary material.

Individual stressor component analyses revealed a consistent pattern: the post-COVID-19 cohort reported significantly higher subjective workload scores, along with elevated fatigue, task complexity, risk perception, concentration demands, work rhythm, and responsibility compared to the PM_{2.5} group. (all $p < .001$), with effect sizes ranging from small to moderate ($d = 0.36–0.51$). Responsibility scores also differed between groups,

though the effect was smaller ($d = 0.17, p = .041$). Notably, the pattern reversed for motivational factors: the PM_{2.5} cohort reported higher intrinsic job interest ($d = -0.33, p < .001$) and greater perceived autonomy ($d = -0.25, p = .001$). These findings indicate that while environmental stressors predominated during PM_{2.5} exposure, psychosocial and cognitive demands were more burdensome during post-pandemic recovery.

4.3 Environmental, Organizational, and Biomechanical Discomfort

Environmental and biomechanical discomfort ratings across four daily activity domains (academic study, assignment completion, social media usage, and household chores) are presented in Table 3. A consistent pattern emerged: the PM_{2.5} cohort reported significantly greater environmental discomfort than the post-COVID-19 cohort across all activities. Specifically, students exposed to elevated PM_{2.5} levels experienced significantly worse air quality, elevated dust exposure, and suboptimal illumination across all four activity types, with effect sizes typically moderate to large ($d = -0.49$ to -0.81). Biomechanical discomfort followed a similar pattern, with the PM_{2.5} group reporting more adverse postures and restricted movement during daily activities. Differences in noise and vibration were smaller and less consistent. These findings indicate that while the post-COVID-19 cohort faced primarily psychosocial and cognitive challenges, the PM_{2.5} cohort contended with a physically burdensome environment affecting comfort and posture across diverse daily tasks.

4.4 Correlational Patterns Between Workload and Stressor Factors

Correlation analyses revealed systematic relationships between subjective workload and stressor dimensions. As illustrated in Figure 1, SWI demonstrated strong positive correlations with central and peripheral fatigue, task complexity, and workload rhythm in both cohorts ($r = 0.40$ – 0.66 , $p < .01$), confirming that cognitive demands and physical fatigue are principal contributors to perceived workload. Conversely, motivational factors exhibited moderate inverse relationships with SWI: higher intrinsic task motivation and greater autonomy were associated with lower subjective workload scores ($r = -0.31$ to -0.42 , $p < .01$), reinforcing the buffering role of motivational resources against excessive workload perception.

Figure 2 extends these findings by depicting correlations between SWI and environmental or organizational factors across activity types. Environmental stressors such as dust and heat demonstrated stronger associations with SWI in the PM_{2.5} cohort, particularly during household and academic tasks, underscoring the multidimensional nature of stress and the capacity of environmental conditions to amplify both mental strain and physical discomfort.

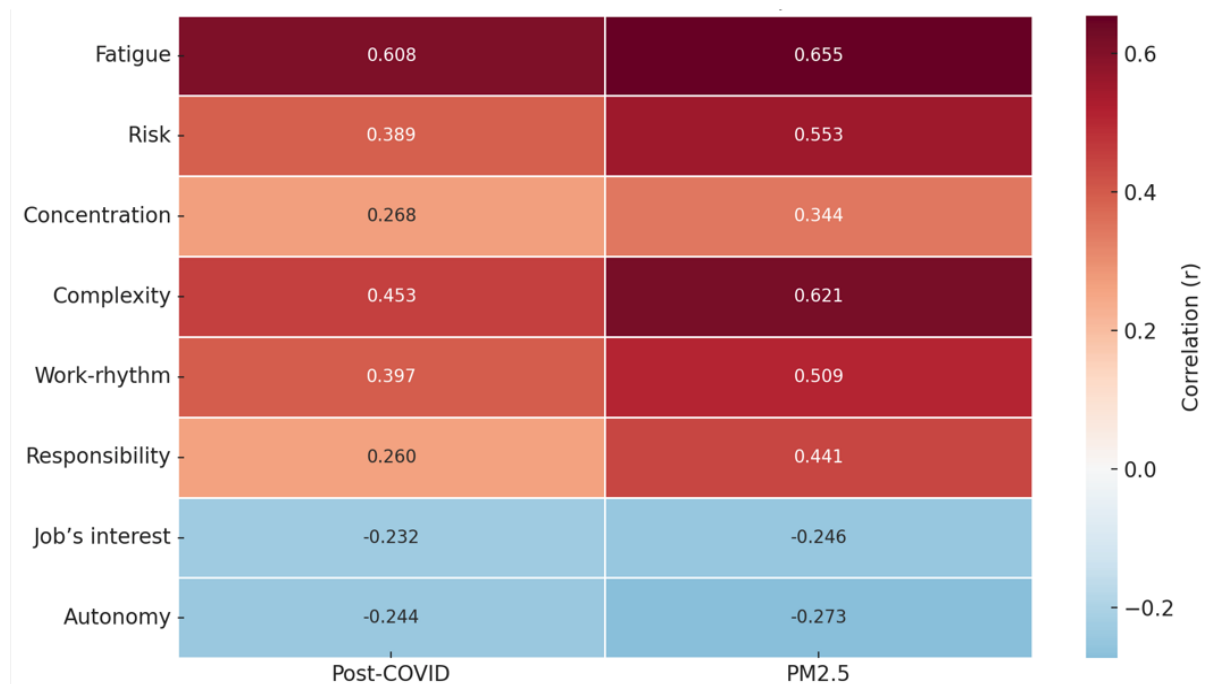


Figure 1 Heatmap of Pearson correlation coefficients between Subjective Workload Index (SWI) and psychosocial work factors in post-COVID-19 and PM_{2.5} cohorts. Red indicates positive correlations; blue indicates negative correlations. All correlations are significant at $p < .05$

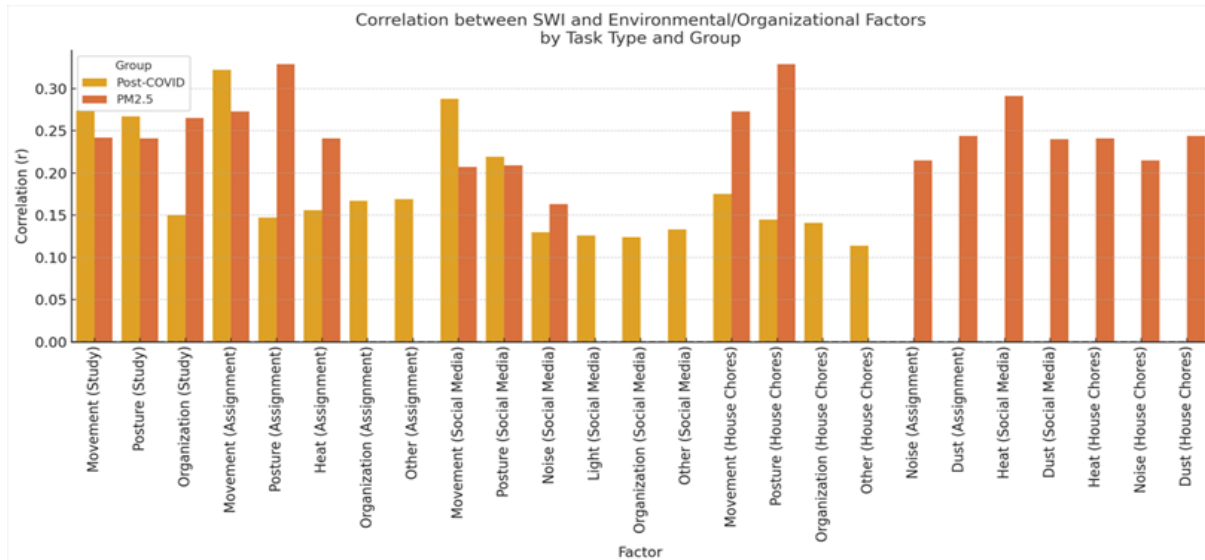


Figure 2 Pearson correlation coefficients (r) between Subjective Workload Index (SWI) and environmental/organizational factors across different task types (study, assignment, social media, and household chores) in the post-COVID-19 and PM_{2.5} exposure groups ($p < .05$)

4.5 Predictors of Physical Performance Under PM_{2.5} Exposure

Multivariable linear regression using the stepwise method identified six statistically significant predictors of handgrip strength normalized by BMI (HG/BMI) within the PM_{2.5} cohort: time ($B = 0.001$), noise ($B = 0.192$), dust ($B = -0.077$), vibration ($B = -0.081$), organizational factors ($B = 0.109$), and gender ($B = 0.206$). The overall model accounted for substantial variance in physical performance ($r = 0.674$, $p < .001$), demonstrating that environmental factors interact with organizational and individual characteristics to shape physical capacity under polluted conditions.

4.6 Physical Performance Assessment

Handgrip strength measurements in the PM_{2.5} cohort were notably low for both hands (left hand: $M = 23 \pm 8$ kg; right hand: $M = 25 \pm 7$ kg), with normalized HG/BMI ratios of 0.41 and 0.42, respectively. According to Thai national fitness standards (Department of Physical Education, 2019), these values fall within the “very poor” category, indicating substantially reduced muscular performance. These findings likely reflect the combined effects of prolonged sedentary behavior, suboptimal ergonomic conditions during indoor confinement, and the physiological consequences of sustained PM_{2.5} exposure.

4.7 Application Usability and User Satisfaction

Usability evaluation demonstrated high acceptability and technical quality of the Find My Stress PWA. Among 372 participants who completed the assessment, internal consistency was excellent (Cronbach’s $\alpha = 0.957$). The highest-rated items included font readability ($M = 3.99$), color scheme suitability ($M = 3.98$), and cross-device compatibility ($M = 3.93$), all on a 5-point scale. These ratings underscore the application’s user-friendly design and technical accessibility, supporting its potential for broader integration into digital health ecosystems.

5. Discussion

This study reveals two distinct stress profiles among university students, shaped by specific environmental and social contexts. Students navigating post-COVID-19 recovery faced predominantly psychosocial and cognitive challenges, whereas those exposed to peak PM_{2.5} pollution encountered primarily environmental and biomechanical burdens. These findings provide important evidence regarding how external crises differentially affect student well-being and underscore the value of context-sensitive stress monitoring tools.

5.1 Contrasting Stress Profiles: Psychosocial Versus Environmental Burden

The post-COVID-19 cohort reported significantly higher subjective workload scores, along with elevated

fatigue, task complexity, risk perception, concentration demands, work rhythm, and responsibility compared to the PM_{2.5} group. This pattern is consistent with evidence that pandemic-related disruptions to academic routines, social networks, and mental health have lasting consequences extending into the recovery period (Dresen et al., 2025; Zhang, 2020). In contrast, the PM_{2.5} cohort experienced greater discomfort related to poor air quality, elevated dust exposure, inadequate illumination, and sustained adverse postures across all daily activities. This shift from psychosocial to environmental and biomechanical strain suggests that severe air pollution episodes generate a distinct pattern of physical discomfort and ergonomic challenges, likely driven by prolonged indoor confinement and suboptimal study environments.

5.2 Biological Plausibility and Mechanistic Evidence

The observed patterns align with a growing body of mechanistic evidence linking PM_{2.5} exposure to cognitive and physical impairments. Short- and long-term fine particulate exposure has been associated with reduced cognitive performance, including deficits in attention, memory, and executive function (Ke et al., 2022). Experimental evidence demonstrates that even brief PM_{2.5} exposure impairs selective attention and emotion recognition within hours (Faherty et al., 2025), directly supporting the SWI framework's cognitive load components. Additionally, epidemiological and mechanistic studies link PM_{2.5} to musculoskeletal strain through pathways including elevated disease risk, mitochondrial dysfunction, and systemic inflammation (Cheng et al., 2024; Ding et al., 2025), plausibly amplifying the perceived biomechanical burden observed in the PM_{2.5} cohort.

5.3 The Protective Role of Motivation and Autonomy

An important finding across both cohorts is the inverse relationship between motivational factors and subjective workload. Students reporting higher intrinsic task motivation and greater perceived autonomy experienced lower SWI scores, even amid significant environmental or psychosocial stressors. This finding is consistent with evidence from organizational psychology and educational research indicating that intrinsic motivation and task ownership buffer against excessive workload perception (Evans et al., 2024; Yaban & Gaschler, 2025). Interestingly, motivational factors were higher in the PM_{2.5} cohort, possibly because environmental stressors while physically uncomfortable do not undermine students' sense of purpose or autonomy to

the same extent as social isolation and pandemic-related anxiety.

5.4 Environmental Context and Physical Performance

The regression analysis demonstrated that physical strength, as measured by HG/BMI, was influenced by a complex interplay of environmental, temporal, organizational, and individual factors. The observed handgrip strength values, classified as "very poor" according to national standards, suggest that sustained exposure to poor air quality combined with sedentary indoor behavior and suboptimal ergonomic conditions may compromise students' muscular performance and functional capacity. These findings are consistent with handgrip strength's established utility as a marker of physical resilience with demonstrated associations with diverse health outcomes (Yoopat et al., 2025).

5.5 Implications for Ergonomic and Motivational Interventions

The convergence of psychosocial and environmental burdens observed in this study underscores the need for integrated, multidimensional interventions. During post-pandemic recovery, universities should prioritize mental health support, peer connection opportunities, and academic reintegration programs. During environmental crises such as PM_{2.5} episodes, interventions should focus on ergonomic optimization, physical activity promotion, and posture-supportive workstation design. Handgrip strength assessment, particularly when normalized by BMI, emerged as a pragmatic and accessible biomarker for monitoring functional capacity, positioning it as a valuable screening tool in digital ergonomics platforms.

5.6 The Find My Stress PWA: A Scalable Digital Solution

The high usability ratings and excellent internal consistency of the Find My Stress PWA support its viability as a scalable platform for real-time, multidimensional stress monitoring in university settings. The application successfully distinguished between psychosocial-cognitive burdens and environmental-biomechanical challenges. Digital health tools of this nature offer advantages over traditional methods by enabling real-time data collection across varied activities, providing immediate personalized feedback, and generating

aggregated data for institutional-level surveillance and targeted interventions.

5.7 Limitations and Future Directions

Several limitations warrant consideration. The cross-sectional design precludes causal inference regarding the relationships between environmental exposures and stress outcomes; longitudinal designs are needed to track within-person changes over time. Individual-level PM_{2.5} exposure monitoring—through portable sensors integrated with the PWA would strengthen inference by reducing reliance on ambient measurements. Incorporating physiological endpoints such as heart rate variability, sleep quality via actigraphy, and salivary cortisol would complement self-reported assessments. Intervention studies employing rigorous pre-registered designs with objective outcome tracking are needed to test whether ergonomic modifications and motivational interventions meaningfully reduce stress under various environmental conditions. Finally, expanding recruitment beyond a single private university would enhance generalizability across diverse geographic and socioeconomic contexts.

6. Conclusions

This cross-sectional study demonstrates that university student stress profiles are context-dependent and multidimensional. During post-COVID-19 recovery (2024), students primarily experienced elevated psychosocial and cognitive workload characterized by heightened fatigue, task complexity, and concentration demands. During peak PM_{2.5} exposure (2025), students faced greater environmental and biomechanical burdens including poor air quality, elevated dust levels, and sustained adverse postures across academic and daily activities.

The Find My Stress Progressive Web Application effectively differentiated these context-specific stress patterns, demonstrating excellent internal consistency (Cronbach's $\alpha = 0.957$) and high user satisfaction. Handgrip strength normalized by BMI emerged as a pragmatic biomarker of functional capacity under combined environmental and occupational stress. Motivational factors particularly intrinsic task interest and autonomy demonstrated protective effects against excessive workload perception across both contexts. These findings support the broader implementation of digital ergonomics tools for institutional stress surveillance and targeted interventions as universities navigate recurring environmental and public health crises.

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8. Abbreviations

Abbreviation	Full Term
AQI	Air Quality Index
BMI	Body Mass Index
CI	Confidence Interval
COVID-19	Coronavirus Disease 2019
HG	Handgrip Strength
HG/BMI	Handgrip Strength Normalized by Body Mass Index
M	Mean
PM _{2.5}	Particulate Matter ≤ 2.5 Micrometers in Diameter
PWA	Progressive Web Application
SD	Standard Deviation
SPSS	Statistical Package for the Social Sciences
SWI	Subjective Workload Index

9. CRediT Author Statement

Pongjan Yoopat: Conceptualization, Methodology, Formal analysis, Investigation, Data curation, Writing – original draft, Writing – review & editing, Validation, Project administration, Resources, Funding acquisition.

Karn Yongsiriwit: Software, Visualization.

Thannob Aribarg: Software.

Nisakorn Julraksa: Project administration, Data curation.

Weerawat Liammanee: Formal analysis, Data curation.

Declaration of Competing Interest

The authors declare no conflicts of interest.

10. References

- Alibudbud, R. (2021). On online learning and mental health during the COVID-19 pandemic: Perspectives from the Philippines. *Asian Journal of Psychiatry*, 66, Article 102867. <https://doi.org/10.1016/j.ajp.2021.102867>
- Bran, S. H., Macatangay, R., Chotamonsak, C., Chantara, S., & Surapipith, V. (2024). Understanding the seasonal dynamics of surface PM_{2.5} mass distribution and source

- contributions over Thailand. *Atmospheric Environment*, 331, Article 120613.
<https://doi.org/10.1016/j.atmosenv.2024.120613>
- Campbell, F., Blank, L., Cantrell, A., Baxter, S., Blackmore, C., Dixon, J., & Goyder, E. (2022). Factors that influence mental health of university and college students in the UK: A systematic review. *BMC Public Health*, 22(1), Article 1778. <https://doi.org/10.1186/s12889-022-13943-x>
- Cheng, B., Pan, C., Cai, Q., Liu, L., Cheng, S., Yang, X., ... & Zhang, F. (2024). Long-term ambient air pollution and the risk of musculoskeletal diseases: A prospective cohort study. *Journal of Hazardous Materials*, 466, Article 133658. <https://doi.org/10.1016/j.jhazmat.2024.133658>
- Chutipattana, N., Le, C. N., & Kaewsawat, S. (2022). Depression, anxiety, and stress during COVID-19 epidemic among public health students in Thailand. *Trends in Sciences*, 19(4), 2577-2577.
<https://doi.org/10.48048/tis.2022.2577>
- Department of Physical Education. (2019). *Manual of Physical Fitness Tests and Standard Criteria for Thai Children, Youth, and Adults*. Ministry of Tourism and Sports. Retrieved from <https://prgroup.hss.moph.go.th/attachments/article/709/ebook02.pdf>
- Ding, Y., Wan, Q., & Liu, W. (2025). Effects of atmospherically relevant PM_{2.5} on skeletal muscle mitochondria: a review of damage mechanisms and potential of exercise interventions. *Frontiers in Public Health*, 13, Article 1615363.
<https://doi.org/10.3389/fpubh.2025.1615363>
- Dresen, V., Sigmund, L., Staggl, S., Holzner, B., Rumpold, G., Fischer-Jbali, L. R., ... & Weiss, E. (2025). Impact of COVID-19 on mental health in nursing students and non-nursing students: A cross-sectional study. *Nursing Reports*, 15(8), Article 286.
<https://doi.org/10.3390/nursrep15080286>
- Evans, P., Vansteenkiste, M., Parker, P., Kingsford-Smith, A., & Zhou, S. (2024). Cognitive load theory and its relationships with motivation: A self-determination theory perspective. *Educational Psychology Review*, 36(1), Article 7.
<https://link.springer.com/article/10.1007/s10648-023-09841-2>
- Faherty, T., Raymond, J. E., McFiggans, G., & Pope, F. D. (2025). Acute particulate matter exposure diminishes executive cognitive functioning after four hours regardless of inhalation pathway. *Nature Communications*, 16(1), Article 1339.
<https://doi.org/10.1038/s41467-025-56508-3>
- Ke, L., Zhang, Y., Fu, Y., Shen, X., Zhang, Y., Ma, X., & Di, Q. (2022). Short-term PM_{2.5} exposure and cognitive function: Association and neurophysiological mechanisms. *Environment International*, 170, Article 107593.
<https://doi.org/10.1016/j.envint.2022.107593>
- Malolos, G. Z. C., Baron, M. B. C., Apat, F. A. J., Sagsagat, H. A. A., Pasco, P. B. M., Aportadera, E. T. C. L., ... & Lucero-Prisno III, D. E. (2021). Mental health and well-being of children in the Philippine setting during the COVID-19 pandemic. *Health Promotion Perspectives*, 11(3), 267-270.
<https://doi.org/10.34172/hpp.2021.34>
- Mungkhunthod, S., Tanthanapanyakorn, P., Khantikulanon, N., & Prasertai, C. (2026). Occupational stress and associated factors among sugarcane farmers in Sa Kaeo Province, Thailand. *Journal of Current Science and Technology*, 16(1), Article 155.
<https://doi.org/10.59796/jcst.V16N1.2026.155>
- Murakami, K., Panuncio-Pinto, M. P., Santos, J. L. F., & de Almeida Troncon, L. E. (2025). Academic and non-academic life stressors and perceived levels of stress in Brazilian undergraduate health professions students. *BMC Medical Education*, 25(1), Article 1164.
<https://doi.org/10.1186/s12909-025-07754-y>
- Noiprasert, S., Butttagat, V., Sittiprapaporn, P., Sivaphongthongchai, A., & Hongsing, P. (2024). Effects of acupuncture on autonomic nervous system parameters and salivary cortisol level among mental stress university students: A pilot randomized controlled trial. *Journal of Current Science and Technology*, 14(2), Article 25.
<https://doi.org/10.59796/jcst.V14N2.2024.25>
- Shafiq, S., Nipa, S. N., Sultana, S., Rifat-Ur-Rahman, M., & Rahman, M. M. (2021). Exploring the triggering factors for mental stress of university students amid COVID-19 in Bangladesh: A perception-based study. *Children and Youth Services Review*, 120, Article 105789.
<https://doi.org/10.1016/j.chilyouth.2020.105789>
- Sutthigoon, W., Chatchumni, M., Thatsiririratkul, R., Kiennukul, N., Rongsri, W., Boonyatham, S., & Chantara, P. (2025). The

- face of crisis: Examining factors affecting nurses' professional values during the COVID-19 pandemic. *Nursing Reports*, 15(11), Article 388.
<https://doi.org/10.3390/nursrep15110388>
- Yaban, E. H., & Gaschler, R. (2025). Autonomous motivation, self-efficacy, and developmental regulation processes in distance education across diverse age groups. *American Journal of Distance Education*, 1-21.
<https://doi.org/10.1080/08923647.2025.2484047>
- Yoopat, P., Deerod, P., & Keakla, S. (2025). Comparative analysis of handgrip strength and handgrip strength-to-BMI ratio among male Thai ultimate frisbee athletes, male university athletes, and male university students: A cross-sectional study. *Journal of Current Science and Technology*, 15(2), Article 109.
<https://doi.org/10.59796/jcst.V15N2.2025.109>
- Yoopat, P., Thoicharoen, P., Liammanee, W., Aribarg, T., Yongsiriwit, K., & Chaisiriprasert, P. (2024). Assessment of work-related stress utilizing the Find My Stress mobile application among university students and adult workers amidst the COVID-19 pandemic. *Journal of Bodywork and Movement Therapies*, 39, 415-422.
<https://doi.org/10.1016/j.jbmt.2024.02.016>
- Zhang, X. (2020). A bibliometric analysis of second language acquisition between 1997 and 2018. *Studies in Second Language Acquisition*, 42(1), 199-222.
<https://doi.org/10.1017/S0272263119000573>