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Behavioral indicators associated with subjective mental fatigue during VDT-based learning activities

Ryota OCHI[a*], Yutaka NAKAMURA[a]
[a]*Information Science and Technology Center, Kyushu Institute of Technology, Japan*
*ochi.ryota940@mail.kyutech.jp

Abstract: This study aims to investigate the relationships between subjective mental fatigue and behavioral indicators during free-form VDT-based learning activities. In the experiments, participants reported subjective mental fatigue and recorded facial video and PC interaction logs during learning activities. In the analyses, after confirming the validity of subjective mental fatigue, we analyzed its relationships with indicators derived from facial video and PC interaction logs. The results showed that indicators derived from PC interaction behaviors were negatively associated with mental fatigue. In contrast, facial indicators, such as mouth-related actions and changes in head rotation angles, were positively associated with it. These results indicate that mental fatigue during free-form VDT-based learning is associated with changes in interaction variability and facial movement patterns. These findings suggest that behavioral regulation gradually changes as fatigue increases.

Keywords: Mental fatigue, VDT, Learning activity, Facial video, PC interaction logs

1. Introduction

1.1 Background

Recently, learning activities using Visual Display Terminals (VDTs), including personal computers (PCs) and tablets, have become prevalent. Mental fatigue during prolonged VDT use is an important issue in learning contexts, as it is associated with reduced engagement and difficulties in self-regulation (Inan et al., 2025; Salmela-Aro et al., 2021). Therefore, monitoring fatigue is important for supporting self-regulated learning by enabling learners to take breaks based on their own conditions.

Methods for assessing fatigue during VDT-based work include self-report questionnaires and physiological measurement devices. These methods are difficult to implement in educational settings due to limitations in real-time measurement and concerns about fairness. To address these issues, this study focuses on automated, non-intrusive measurement methods using data from PCs to establish real-time, equitable fatigue assessment in educational settings (Ochi, 2026).

Furthermore, many previous studies on fatigue assessment during VDT-based work have mainly been conducted in laboratory environments using artificially designed tasks. He et al. (2026) noted that findings from these environments might not be sufficiently useful in real-world activities. As a result, the behavioral indicators for assessing mental fatigue that emerge during real-world VDT-based work remain insufficiently understood.

Additionally, many previous studies on VDT-related fatigue assessment employ approaches using a single modality. These methods are susceptible to individual differences and environmental noise, which raises concerns about their robustness and generalizability in real-world settings (He et al., 2026).

Taken together, for fatigue assessment aimed at practical deployment in educational settings, it is important to clarify how multimodal and non-contact indicators, such as facial video and PC interaction logs, relate to mental fatigue in real VDT-based learning activities.

1.2 Mental Fatigue and Related Work

ISO 10075-1 defines mental fatigue as a temporary decline in mental and physical functional efficiency depending on preceding mental strain. This manifests as feelings of tiredness, declines in performance, and varies depending on individual preconditions. On the other hand, previous studies have shown that subjective fatigue and performance changes are partially independent phenomena and do not necessarily coincide (Kluger et al., 2013). Additionally, according to compensatory control theory, individuals can maintain performance by exerting extra effort, especially in complex and realistic cognitive tasks, even when they become fatigued (Muñoz-de-Escalona et al., 2020). In such situations, evaluating subjective mental fatigue becomes particularly essential.

While several studies have explored estimating mental fatigue using multimodal data that combine indicators derived from facial video and PC interaction logs (e.g., Dai et al., 2023; Virk et al., 2023), they primarily rely on artificially designed tasks. Although some studies (e.g., Silveira et al., 2025) have been conducted in settings closer to real learning environments, the learning activities were still constrained to predefined task types.

In this context, the purpose of this study is to investigate the relationships between subjective mental fatigue and indicators derived from facial video and PC interaction logs during free-form VDT-based learning activities. In this study, “free-form” means that learners freely select learning content rather than perform fixed tasks. We adopted this setting because predefined tasks may produce task-specific behavioral patterns, whereas free-form learning better reflects real-world learning activities.

2. Experiment

A total of 34 undergraduate and graduate students participated in the experiment. All participants joined the experiment after receiving an explanation of the research purpose and providing informed consent. We included data from 26 participants in the analysis, for whom we successfully recorded both facial video and PC interaction logs without missing data (21 males and 5 females; mean age = 19.35 ± 1.39 years). As VDT-based learning activities, participants engaged in self-selected, free-form learning tasks using their own PCs. To minimize excessive gaze shifts or large head movements, we instructed participants to perform tasks using a PC. We also prohibited activities unrelated to learning, such as administrative work. Participants rated mental fatigue and concentration on a 50-point scale (1 = very low, 50 = very high) and the need for a break on a 6-point Likert scale. We administered subjective questionnaires every 15 minutes during the learning activities. Each session consisted of a 60-minute learning activity, and participants completed subjective evaluations every 15 minutes. Participants took a 10-minute break after a session. Participants completed this session twice per day, and the entire procedure spanned two non-consecutive days. The experiment took place in a lecture room, and participants sat at approximately 40–60 cm from their PC screens. Participants used their own PCs to record facial video and PC interaction logs. The PCs ran Windows and had a built-in camera with a resolution of at least 1080p. The built-in camera recorded facial video at 1920 × 1080 pixels and 30 fps. PC interaction logs included keyboard, mouse, and window-related data.

3. Analysis Methods

We examined the accumulation and reversibility of mental fatigue, as well as its associations with related constructs (concentration and need for breaks), using within-participant statistical analyses.

Next, we extracted behavioral indicators from keyboard, mouse, and window activity logs recorded during the learning activity, such as keystrokes, cursor movement, and tab switching. After computing each indicator using 1-minute windows, we aggregated them by calculating the mean and standard deviation (SD) for each 15-minute interval. We also extracted indicators about head rotation, action units (AUs), and gaze directions using OpenFace, an open-source toolkit for facial behavior analysis (Baltrušaitis et al., 2018). We processed facial videos recorded during the session to compute either the mean value or the temporal variation of each indicator within each 15-minute interval.

To identify behavioral indicators consistently associated with subjective mental fatigue, we selected indicators that met predefined criteria emphasizing within-participant changes. These criteria also reduce short-term task-specific fluctuations by aggregating over time. First, we matched subjective mental fatigue reported at 15-minute intervals with behavioral indicators aggregated over the preceding 15-minute interval. Then, we computed a pooled within-person correlation by centering each indicator and fatigue rating within participants and calculating correlations using the aggregated within-person deviations across all participants. We selected an absolute correlation value of 0.15 as a reference for the effect size to focus on potentially meaningful associations. Second, to ensure consistency across individuals, we defined directional agreement as the proportion of participants whose correlation sign matched the group-level direction. We selected indicators that showed directional agreement of at least 70%. This criterion reduced the influence of participant-specific effects that may arise in free-form learning activities. Third, we assessed statistical significance using false discovery rate correction across indicators and selected only indicators with q-values below 0.05. Fourth, we selected indicators only when at least six valid 1-minute windows were available within a 15-minute interval. This ensured that each aggregated indicator reflected sufficient temporal coverage. It also allowed us to tolerate partial data loss.

4. Result and Discussion

Mental fatigue increased over time ($p < 0.01$) and decreased after breaks ($p < 0.01$) and was correlated with the need for a break ($r = 0.67$, $p < 0.01$) and concentration ($r = -0.42$, $p < 0.01$). These results support the validity of subjective mental fatigue ratings from three perspectives: accumulation over time, reversibility with breaks, and associations with related constructs.

Next, Table 1 shows the indicators adopted based on the criteria. For indicators derived from PC interaction logs, the 15-minute SD of excess mouse movement distance (defined as the difference between actual cursor path length and straight-line distance) and rapid tab-switching intervals (i.e., variability of mean intervals between rapid tab switches ≤ 3 seconds) decreased with increasing mental fatigue. This suggests reduced exploratory and flexible interaction behaviors. These changes likely reflect increased effort costs for maintaining diverse interactions. This leads to a shift toward more economical interaction styles under fatigue.

Table 1. Relationship between mental fatigue and behavioral indicators.

Indicator	Correlation	q-value	Directional agreement	N (valid intervals)
15-minute SD of excess mouse movement distance	-0.156	0.020	0.769	411
15-minute SD of rapid tab-switching interval	-0.171	0.040	0.720	247
Mean intensity of AU25 (Lips Part)	0.203	0.001	0.808	416
Change in head rotation angles (X-axis)	0.204	0.001	0.731	416
Change in head rotation angles (Z-axis)	0.209	0.001	0.846	416

On the other hand, indicators derived from facial videos positively correlated. AU25 (Lips Part) was associated with yawning and oral relaxation, suggesting reduced arousal accompanying mental fatigue. Changes in head rotation angles along the X and Z axes increased with fatigue, indicating that postural stability decreased. These changes likely reflect both reduced precision in postural control due to reduced arousal and an effort-adjustment process in which posture maintenance is downregulated. Overall, the results suggest that mouth-related actions and changes in head rotation angles indicate reduced arousal and effort adjustment during mental fatigue.

Collectively, these results indicate that mental fatigue is characterized by a shift in effort allocation toward less variable and more economical behavioral regulation. Indicators derived from PC interaction logs and those derived from facial video appear to capture complementary aspects of this process, thereby providing insight into how fatigue manifests as changes in behavioral regulation during real-world learning activities.

This study has several limitations. First, because the participant sample was relatively homogeneous (undergraduate and graduate students), this limits the generalizability of the findings. Second, because participants engaged in free-form learning activities, differences in task types may have influenced the behavioral indicators. Although we temporally aggregated behavioral indicators and used analytical procedures to mitigate sensitivity to momentary task-specific fluctuations, we cannot fully eliminate residual task-related influences. Accordingly, the present findings should be interpreted as reflecting general behavioral tendencies associated with increasing mental fatigue across diverse learning contexts. They should not be interpreted as effects entirely independent of task structure. Future research should include a broader and more diverse participant pool, encompassing learners of different ages, educational backgrounds, and cultural contexts, to improve the reliability, validity, and generalizability of behavioral indicators of mental fatigue. In addition, incorporating task-aware modeling approaches that explicitly account for task characteristics will be necessary. This will help disentangle task-related effects from fatigue-related behavioral changes. It will also help clarify their independent contributions. Furthermore, objective approaches, such as fatigue labeling from facial video, may complement subjective measures and provide a more comprehensive assessment.

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