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Validating Stress Induction for Spaceflight Scenarios: A Manipulation Check Across Acute Stressor Types in Simulated Task Environments

Jeanne Nicole[1], Raphaëlle Giguère[1,2], Danielle Benesch[3], Cindy Chamberland[1], Tanya S. Paul[3], Denis Ouellet[1], Alexandre Marois[1,3], and Sébastien Tremblay[1]

[1]Université Laval, Québec, QC, G1V 0A6, Canada
[2]VITAM, Québec, QC, G1J 2G1, Canada
[3]Thales cortAIx Labs, Montréal, QC, H4S 2C2, Canada

ABSTRACT

Stress is a multifaceted phenomenon that affects several cognitive functions, including decision-making, memory and attention. In high-risk operational environments, these impairments can have critical safety implications, making it essential to continuously and non-invasively assess stress levels in human operators. Wearable monitoring technologies such as smart shirts and smartwatches now allow for continuous measurement of physiological stress markers, including heart rate (HR) and respiration rate (RR). Advances in artificial intelligence (AI) and machine learning enable the development of detection models that estimate stress based on physiological signals. These tools are increasingly integrated into Human-Autonomy Teaming systems (HAT), allowing real-time interpretation of human states to support decision-making and prevent stress overload. However, different types of stressors can elicit distinct physiological and subjective responses. To design adaptive and context-specific stress detection models, a clearer understanding of these variations is required. The present study conducted a manipulation check to validate three stress-inducing procedures and to compare their effects on subjective and physiological responses. A total of 120 participants were randomly assigned to one of three conditions: time pressure alone, time pressure with noise, or time pressure with social evaluation. Each participant completed a baseline, tutorial, two low-stress scenarios, and one stressful scenario using the OpenMATB task. Participants completed questionnaires on stress and workload following each task, while HR and RR were recorded throughout. Mixed ANOVAs revealed significant increases in subjective and physiological indicators during the stress scenarios, confirming effective stress induction. These findings provide a foundation for developing AI models capable of real-time stress detection in high-risk environments.

Keywords: Stress, Performance, Biometrics, Wearable sensors, Space mission simulation, Human-autonomy teaming

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INTRODUCTION

Stress is a complex and multifaceted phenomenon that plays a central role in both psychological and physiological functioning (Giannakakis et al., 2019). Acute stress refers to a type of stress triggered by a specific event that feels new or is unpredictable (Arsalan et al., 2023). It can lead to many cognitive, emotional and physiological consequences (Crosswell & Lockwood, 2020). In experimental research, acute stress is often induced using manipulations such as increased workload, time pressure and social evaluative threat (Dismukes et al., 2015). The stress response consists of physiological and behavioural changes triggered by a stressor, defined as any stimulus that disrupts the body's dynamic equilibrium (also known as homeostasis; Chu et al., 2025; Selye, 1984). When a potential threat is detected, the amygdala signals the hypothalamus, thus activating two stress response systems. The fast-acting sympathetic-adreno-medullary axis releases adrenaline, increasing heart rate, respiration, blood pressure, and alertness. The slower hypothalamic-pituitary-adrenal axis releases cortisol, sustaining arousal and energy availability (Chu et al., 2025).

Although the stress response is adaptive and essential for survival, considerable evidence suggests that it can negatively impact cognitive functioning (Dismukes et al., 2015). Notably, stress has been shown to impair attention (Crump et al., 2021), memory (Schwabe, 2025) and decision-making (Yu, 2016). These cognitive impairments present significant concerns in high-risk domains such as aerospace and aviation, where optimal cognitive performance is essential. In such contexts, stress is inherent and unavoidable. For instance, astronauts are exposed to numerous stressors during spaceflight, including isolation, excessive workload, microgravity and noise (Giguère et al., 2025a; Yin et al., 2023). These stressors are major contributors to safety breaches and, at times, fatal accidents (Dismukes et al., 2015). Findings from aviation accident analyses highlight this risk: among 212 flight crew errors examined across 12 major airline accidents, a large proportion was associated with failures in attention management, working memory limitations, and decision-making disruption, all of which are exacerbated by acute stress (Dismukes et al., 2015). In high-risk scenarios, strategies to reduce the impact of acute stress on cognitive performance are essential. One promising approach is human-autonomy teaming (HAT), in which human operators and autonomous agents work interdependently, sharing tasks and adapting to each other's strengths and weaknesses (Lyons et al., 2021). By integrating near real-time stress monitoring into HAT models, autonomous systems could detect signs of operator overload and adjust task load (Korivand et al., 2024).

Stress monitoring can rely on both subjective and objective indicators. Subjective self-reports of stress are generally obtained using standardized and validated questionnaires, which contain one or multiple questions about the respondents' experiences of stress (Dorsey et al., 2022). These questionnaires include, for example, the Acute Stress Disorder Scale (Bryant et al., 2000) and the Visual Analog Scale of Stress (VAS-S; Lesage et al., 2012). Objective indicators include several types of measures, among them physiological measures which assess internal bodily responses using sensors, such as heart rate (HR) and respiratory rate (RR; Arsalan et al., 2023). Since most physiological measures are involuntary and regulated by the autonomic nervous system, they are often considered reliable indicators of stress (Giannakakis et al., 2019). Their use enables continuous monitoring with minimal demands and interruptions, making them particularly appropriate for monitoring operator state in adaptive systems (Teo et al., 2018). Ambulatory wearable monitoring devices, such as smart shirts (e.g., BioHarness or Hexoskin) and smartwatches (e.g., Fitbit), can track physiological activity in a non-invasive manner, which is especially valuable in dynamic environments. Integrated into adaptive HAT systems, detection models using these signals would allow for real-time interventions, augmenting performance and increasing psychological safety in multiple high-risk domains such as aviation and space exploration (Lyons et al., 2021). In fact, space health monitoring is already transitioning toward increasingly autonomous systems, designed to support crews during missions where contact with Earth is limited (CSA, 2021). These systems will eventually rely on wearable sensors to track indicators such as exercise and sleep, with artificial intelligence (AI) analysing the data in real time to enable quick interventions aimed at preserving health and psychological well-being (CSA, 2021).

Study Goal

To be applicable in real-world contexts, stress detection models must demonstrate strong generalizability (Prajod et al., 2024). Yet, generalizability is often limited by the type of stressor, as different stressors may elicit distinct stress responses and, potentially, different physiological responses (Prajod et al., 2024). Systematically examining physiological responses across multiple stressors within the same experimental design could help characterize their unique and shared signatures. This could help build stress models that are more ecologically valid and, in the end, make HAT systems more effective. Building on this reasoning, the current paper takes preliminary steps toward the identification of physiological signatures associated with different types of stressors. This study provides a manipulation check for a stress-induction protocol using distinct types of stressors in a context involving multiple tasks typically faced by operators in aeronautical and aerospace situations.

To reach this goal, we asked participants to complete the Open Multi-Attribute Task Battery (OpenMATB; Cegarra et al., 2020). Different levels of stress scenarios (low and high) were presented. The high stress scenario could either involve: (1) time pressure (single cognitive stressor); (2) time pressure combined with a distracting noise (multiple cognitive stressors); and (3) time pressure with a social-evaluative component (social and cognitive stressor combination). Continuous physiological monitoring was conducted using a BioHarness Zephyr chest strap and a Fossil Gen 5 smartwatch. As a manipulation check, we aimed to determine whether all three conditions successfully induced stress during the high stress scenario, and whether different types of stressors elicited distinct subjective and physiological response patterns. It was hypothesized that all three conditions would elicit a stress response, reflected by higher subjective workload and stress scores, as well as increased HR and RR. Additionally, at a more exploratory level, we anticipated that preliminary analyses might reveal condition-dependent differences in stress response patterns across stressor types.

METHODS

Participants

One hundred and twenty participants were recruited for this study. Participants were 18 years or older, French speaking students or employees from Université Laval (63 women, 55 men, 2 non-binary individuals; mean age = 30.23 years; *SD* = 12.82). All participants had normal or corrected-to-normal vision and hearing, no reading difficulties and no diagnosed neurological disease. Participants were healthy and reported no clinical diagnosis that could influence their physiological response to stress. Informed consent was obtained twice: initially with a general description to minimize bias, and again after debriefing with the full study purpose. The study was approved by the Research Ethics Committee of Université Laval (No 2024-335 A-1 / 31-01-2025).

Materials and Procedure

Before beginning the first task, participants completed a brief sociodemographic questionnaire including age, gender, education level, physical fitness level and employment status. After completing this questionnaire, a baseline measure was obtained by instructing participants to fixate on a cross displayed on a white screen for a duration of five minutes while physiological data were recorded. Throughout the experiment, HR and RR were continuously monitored using the BioHarness. For this study, we used features directly provided by the device and no further preprocessing was done. Participants were then asked to perform tasks of the OpenMATB (Cegarra et al., 2020) which requires participants to simultaneously perform four tasks. The task typically involves: (1) a monitoring task; (2) a tracking task; (3) an auditory communication task; and (4) a resource management task. Since the OpenMATB environment is configurable, only three of the four tasks were administered in this study. The tracking task was omitted to avoid inducing excessive mental workload, which could lead to participant disengagement.

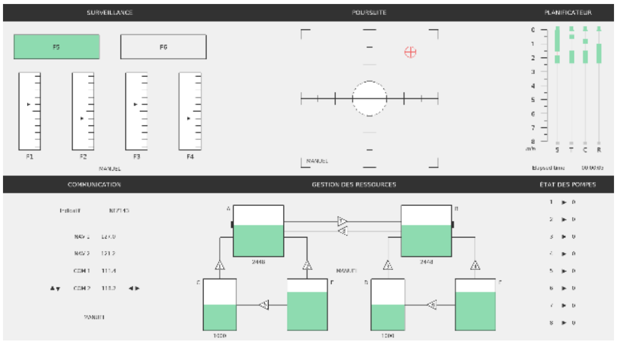

Figure 1: Screenshot of the OpenMATB task interface (Cegarra et al., 2020).

Participants completed four OpenMATB scenarios. The first scenario was the tutorial and was programmed to help the participants to familiarize themselves with the subtasks. The second, considered easy, was not intended to induce stress. The third was the only one where participants should feel stressed. The fourth was another easy scenario that was not expected to elicit stress. Participants were randomly assigned to one of three conditions (n = 40 per condition): a single stressor condition, where the only stressor was the task itself, a multiple stressors condition, where time pressure was combined with a noise that was generated to stress the participants, and a social stress condition, where time pressure was combined with the presence of an evaluator, a procedure inspired by the Trier Social Stress Test (TSST; Kirschbaum et al., 1993). In the middle of each scenario, the participants had to stop the task for 60 seconds and were asked to briefly describe their current situation. This data is not analysed here but will be the subject of other studies. After each task, participants rated their level of stress on a VAS-S (Lesage et al., 2012) scale with values ranging from 0 to 10. They also completed the NASA-Task Load IndeX (NASA-TLX; Hart & Staveland, 1988) to report their subjective workload level.

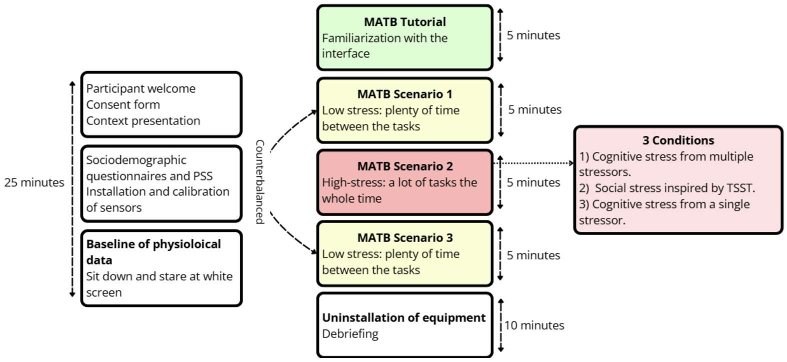

Figure 2: Experimental protocol with three stress conditions.

RESULTS

We analysed the differences in self-reported stress (VAS-S), self-reported workload (NASA-TLX), and mean HR and RR within each scenario and condition (see Giguère et al., 2025b for the dataset). To this end, we conducted a series of 3 (Condition: multiple stressors, social stress, single stressor) × 5 (Scenario: baseline, tutorial, low-stress 1, stressful, low-stress 2) mixed analyses of variances (ANOVAs). When the sphericity assumption was violated, we report Greenhouse-Geisser corrected p-values. Bonferroni corrections and Dunn's method were performed for multiple comparisons and simple main effects analysis, respectively (Dunn's corrected value for simple effect tests = .01875). Finally, Spearman correlations were carried out across all measures.

Subjective Measures

Figure 3 presents the VAS-S scores as a function of the Condition and Scenario. The 3 × 5 mixed ANOVA conducted on the VAS-S revealed a significant main effect of the Scenario, $F(4, 468) = 97.923$, $p < .001$, $\eta^2_p = .46$. but no main effect of Condition, $F(2, 117) = 0.740$, $p = .479$, $\eta^2_p = .01$, nor a significant interaction, $F(8, 468) = 1.275$, $p = .264$, $\eta^2_p = .02$. Post hoc comparisons showed that the stressful scenario elicited significantly higher scores than other scenarios (*ps* < .001). Baseline scores were significantly lower than those from all other scenarios (*ps* < .001).

Regarding the NASA-TLX scores (see Figure 4), the analysis revealed a significant main effect of Scenario, $F(4, 468) = 157.739$, $p < .001$, $\eta^2_p = .57$. Neither the main effect of Condition, $F(2, 117) = 0.668$, $p = .515$, $\eta^2_p = .01$, nor the interaction, $F(8, 468) = 1.639$, $p = .149$, $\eta^2_p = .03$, reached significance. As with VAS-S, post hoc analyses showed that the stressful scenario produced higher scores than all other scenarios (*p*s < .001). Baseline and tutorial scores were also lower than all other experimental scenarios (*p*s < .001).

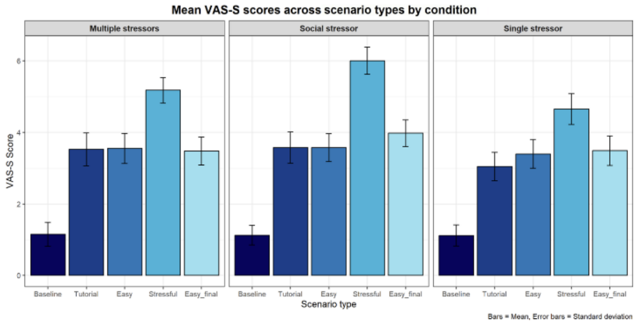

Figure 3: Depiction of the VAS-S mean scores across scenarios and conditions. Error bars represent the standard error of the mean.

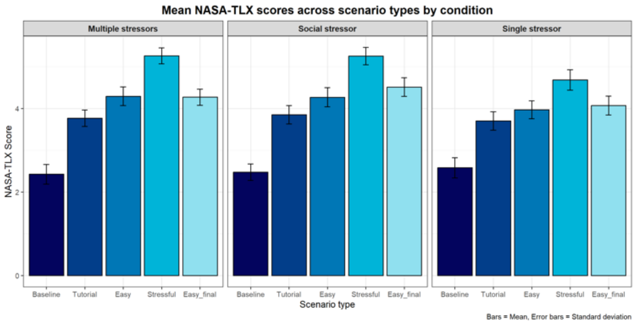

Figure 4: Depiction of the NASA-TLX mean scores across scenarios and conditions. Error bars represent the standard error of the mean.

Objective Measures

The analysis showed a significant main effect of Scenario regarding mean RR measures, $F(4, 468) = 34.808$, $p < .001$, $\eta^2_p = .23$ (see Figure 5). However, the main effect of Condition, $F(2, 117) = 0.763$, $p = .468$, $\eta^2_p = .01$, and the two-way interaction did not reach significance, $F(8, 468) = 1.499$, $p = .202$, $\eta^2_p = .03$. Post hoc analyses showed that the stressful scenario resulted in higher scores than all other scenarios (*ps* < .001) and baseline RR measures were lower than all others (*ps* < .001).

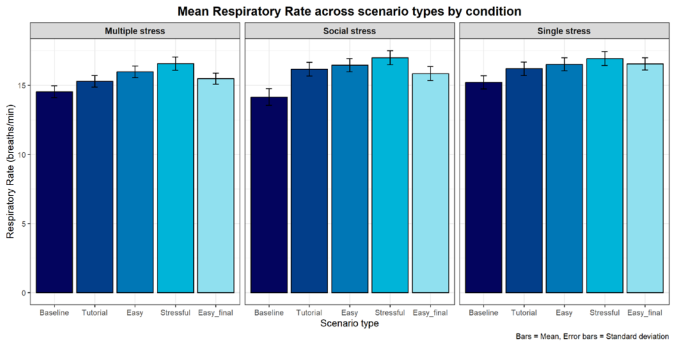

Figure 5: Depiction of the mean respiration rate (RR) across scenarios and conditions. Error bars represent the standard error of the mean.

Regarding the mean HR values (see Figure 6), the analysis revealed a significant main effect of Scenario, $F(4, 468) = 8.944$, $p < .001$, $\eta^2_p = .07$, and a significant Scenario × Condition interaction, $F(8, 468) = 3.623$, $p = .004$, $\eta^2_p = .06$, both indicating modest effect sizes. No main effect of Condition was observed, $F(2, 117) = 2.184$, $p = .117$, $\eta^2_p = .04$. Decomposition of the interaction showed that, within each of the three conditions, at least one significant difference could be found across the five scenarios (*Fs* > 5.059, *ps* < .001). Within the Multiple stress condition, the mean HR measured during the second easy scenario was significantly lower than the one observed in the baseline ($p = .007$) and in the tutorial ($p = .011$). In the social stress condition, the stressful scenario induced a higher mean HR compared with the two easy scenarios (*ps* < .001). In the single stressor condition, the mean HR was lower in the second scenario compared with the HR measured during baseline ($p = .020$). Within each scenario, the differences between conditions did not reach significance once Dunn's correction were applied (*Fs* < 3.551, *ps* > .032).

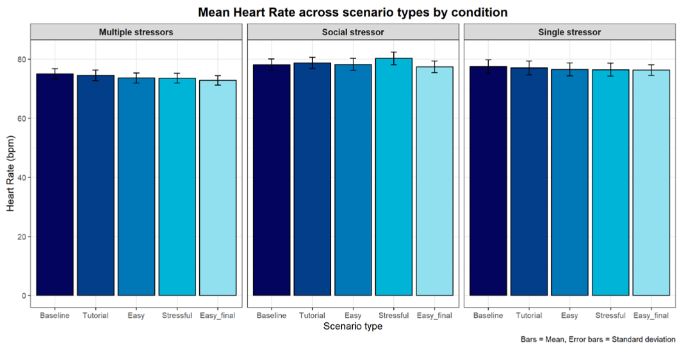

Figure 6: Depiction of the mean heart rate (HR) across scenarios and conditions. Error bars represent the standard error of the mean.

Relationships across Subjective and Objective Measures

Spearman's rank-order correlations were conducted to examine the relationships between subjective stress (VAS-S), perceived workload (NASA-TLX), RR and HR, all averaged across the different scenarios. A strong, positive relationship was found between VAS-S and NASA-TLX scores, $r_S = .795$, $p < .001$. RR showed a weak but statistically significant positive correlation with NASA-TLX scores, $r_S = .180$, $p = .049$. All other correlations failed to reach significance.

DISCUSSION

The aim of the present study was to conduct a manipulation check to validate the stress induction procedure and to perform preliminary analyses assessing the subjective and physiological responses across the different stress conditions. Participants completed four MATB-II tasks, including one scenario designed to induce stress under different conditions (time pressure, time pressure with noise, or time pressure with a social-evaluative component). Throughout the task, subjective stress and workload were assessed using the VAS-S and the NASA-TLX, while continuous physiological activity (HR and RR) was recorded.

Results showed significant main effects of scenario on the VAS-S, NASA-TLX, HR and RR, indicating that participants reported higher stress and workload in the high-stress scenario, which also produced modest increases in HR and larger effects on RR. These results confirm that the stress induction method was effective, consistent with prior studies showing that MATB-II tasks can reliably induce stress (Kennedy & Parker, 2017; Nuamah, 2024).

With the stress manipulation validated, preliminary analyses were conducted. Correlation analyses revealed a strong relationship between NASA-TLX and VAS-S. RR showed only weak correlations with NASA-TLX, while HR showed no correlations. This is in line with previous studies, showing weak correlations between subjective and objective measures (Hilger et al., 2024). Mixed ANOVAs indicated that VAS-S, NASA-TLX and RR did not differ across conditions, suggesting that the type of stressor did not significantly impact the stress response. In contrast, HR showed a different pattern, with only the social stress condition producing a noticeable distinction between the stressful scenario and the easier ones. This pattern suggests that HR may be particularly sensitive to social-evaluative stress, which is consistent with previous findings showing that cardiovascular responses are activated in socially threatening situations (Hellhammer & Schubert, 2012; Kirschbaum et al., 1993). By comparison, RR and subjective measures appeared to capture overall stress levels but were not sensitive to the differences between stressor types. These results suggest that different stressors may elicit distinct physiological signatures. However, these findings remain preliminary, particularly given the minimal preprocessing. Replications across different samples are essential to validate these patterns and improve the generalizability of our results. Understanding these variations in stress responses to different stressors is key to building more accurate stress detection models. This has important implications for the development of adaptive, context-sensitive models that can generalize across real-world settings, particularly in high-stakes environments, where operators are exposed to multiple sources of stress. In applied contexts such as HAT, this would allow for more tailored and effective interventions, which would ultimately reduce errors and accidents in high-risk environments.

CONCLUSION

In conclusion, this study demonstrates that the experimental manipulation successfully induced stress in participants, as shown by both self-reported and physiological measures. This confirms that our protocol can effectively elicit stress responses and may therefore support the development of HAT models. Furthermore, the observation that distinct stress protocols produced variations in both physiological and subjective responses emphasizes the importance of accounting for context-dependent patterns in stress response to develop accurate and generalizable stress models, applicable to high-risk settings.

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