Response to Reviewers Comments

Please find attached the revised and resubmitted version of our manuscript sensors-3762887.

The authors would like to thank the Editor-in-Chief, Associate Editor, and Reviewers for their time and effort spent throughout the review process. Their comments and suggestions proved very valuable in enhancing the quality of the manuscript.

A point-by-point description of changes made to the manuscript in response to the review comments can be found below.

Reviewer 1 Comments and Authors' Response

This article proposes a cognitive monitoring system utilizing vibration and acceleration sensors, effectively highlighting the critical role of cognitive workload (CW) regulation in enhancing human performance, reducing errors, and supporting overall well-being. The importance of CW monitoring is well-established, and the limitations of current methods are articulated. The introduction of a novel MCG-based approach as a potential solution is commendable. While the hardware implementation appears robust and the measured data demonstrates sound acquisition, the argumentation could benefit from a more diverse range of examples and a more thorough exploration of potential limitations and practical considerations.

Thank you for your comments to help us improve our paper. We have addressed your concerns below and in the revised manuscript.

1. Specifically, the discussion lacks sufficient depth in exploring the applicability of this approach across various cognitive tasks and real-world scenarios. Further elaboration on the potential challenges and trade-offs associated with this method would strengthen the paper's overall impact. Expanding the illustrative examples to encompass a wider spectrum of cognitive workloads would also enhance the persuasiveness of the proposed solution.

We have revised Section 4 of the manuscript to include the following discussion: "As is expected, CW can manifest in many contexts beyond the scenarios explored in this pilot study. The selection of the subject scenarios relied on paradigms that have been widely used in the literature to reliably modulate the level of mental effort [1], while the choice of having a controlled laboratory setting arises from the fact that we want to track changes in mHRV solely due to CW. Other memory/cognitive tasks in controlled environments are expected to yield similar results: even if with different intensities, mHRV is expected to drop whenever CW increases. Beyond these scenarios, our MCG approach should, in principle, apply to any task that triggers an autonomic response. For instance, demanding cognitive tasks in safety-critical domains, such as air-traffic control or surgical training, have been shown to tax cognitive resources and mHRV [2]. Likewise, tasks in healthcare (e.g. concussion recovery exercises), education (exam-taking, tutoring), gaming, and immersive training could all benefit from workload monitoring [3][4]. However, applying the proposed approach directly in real-world scenarios would introduce extra variables that might impact mHRV , i.e., mHRV being influenced by several factors beyond CW, such as stress or fitness levels [5]. As such, for this proof-of-concept study, the experimental scenarios were carefully chosen to mimic real-life activities while at the same time limiting external variables that might hinder the mHRV. By contrast, in uncontrolled environments, cognitive load changes might be confounded by other stressors. Any real-world system must account for these."

2. While the hardware implementation appears promising and the data acquisition seems sound, the argument lacks a diverse range of examples and exploration of potential limitations. It would be beneficial to expand on the practical applications and address potential challenges.

We have revised Section 4 of the manuscript to include the following discussion: "In summary, even though the proposed MCG sensor can be used wherever continuous, unobtrusive monitoring of CW is needed, such as applications that include safety monitoring (e.g. warning drowsy or cognitively overloaded drivers/pilots), workplace optimization (e.g., measuring staff workload in manufacturing or control-room environments), and consumer devices (e.g., games or virtual reality systems that adapt to user effort), it is still in the testing stage. It currently requires a snug chest belt and multiple amplifiers, which may not be convenient for all-day wear. Furthermore, it lacks an adequate motion-artifact removal algorithm, making it susceptible to excess motion. Future research should miniaturize and integrate the coils and electronics into a lightweight form factor as well as upgrade the system to address motion artifacts and potentially other confounders."

3. The paper lacks a comparative analysis with existing methods. Simply monitoring participant responses to a few stimuli doesn't fully address the core problem of cognitive workload that the paper aims to solve. Clarifying the contribution to the field would strengthen the paper's central message.

We have revised Section I to provide a more in-depth review of existing methods for monitoring CW.

Specifically, the revised Introduction now states that: "ElectroEncephaloGraphy (EEG), MagnetoEncephaloGraphy (MEG), functional magnetic resonance imaging (fMRI), positron emission tomography (PET), and eye tracking/pupillometry are the most common physiological measures of CW. EEG directly captures the brain's electrical activity through electrodes positioned on the scalp. This method tracks variations in CW over time and delivers results with high temporal precision [6]. MEG measures the magnetic fields generated by the brain's electrical activity. It has shown to achieve similar accuracies as EEG [7]. fMRI detects changes in blood flow related to neural activity. It measures the signal that is dependent on blood oxygenation level and has shown to monitor brain activity with high spatial resolution [8] [9]. PET observes metabolic processes in the brain. It can monitor dopamine receptors at rest and while performing a cognitive task [10]. Task-evoked pupillary responses (TEPR) have also shown to effectively estimate the cognitive effort involved in completing a task [11]. However, although the aforementioned techniques have shown to be effective, they can be very complicated to construct and operate, or very expensive to obtain."

The revised Introduction also states that: "In summary, the key advantage of our work is leveraging MCG as a completely passive cardiac measure for CW. Unlike previous technologies for CW monitoring, our approach requires no skin contact; it senses the heart's magnetic field directly. This enables continuous monitoring without electrode setup or skin irritation. Furthermore, we operate in normal ambient conditions (no shielding), which is novel. Also, the setup is very cheap to build and operate, as opposed to PET and MEG. Aside from the hardware aspects, another key contribution of this work lies in the separation of changes in HRV from CW and PA. Although literature has confirmed the relationship between changes in CW and HRV, no published work exists that tracks the changes back to CW."

4. The sample size of 10 healthy adults (ranging from adolescence to middle age) may limit the generalizability of the findings. Further discussion on the scope and applicability of this approach to a broader population would be valuable.

We have revised Section 2.4 to clarify that: “For this proof-of-concept study, participants were selected as healthy (i.e., no cardiac conditions) to ensure that changes in mHRV were specifically attributed to CW. This is important because pre-existing cardiac conditions can significantly affect HRV. For example, pathological arrhythmias or heart disease often reduce HRV and alter its pattern [16]. By restricting to healthy adults, we ensured our HRV changes reflected cognitive load rather than underlying pathology. To determine the sample size of human subjects for validation, we based our decision on previous studies of CW monitoring, which included 10[1], 16 [12], 12 [13], 9 [14, 15], and 11[16] participants.”

We have also revised Section 4 with the following discussion: “Though the participant sample size is relatively small and the population is not widely representative, all the subjects revealed a decreasing trend in HRV between Scenarios 1 and Scenarios 2. These results are consistent with those observed for different participants and different CW tasks in [17]. Hence, adding more subjects is not expected to affect this result and should be generalizable. The addition of box plots and statistical tests, rather than just individual results, also make our results more statistically valid and generalizable. A more extensive study with more patients (including BMI, sex, and health status considerations) will be performed in the future. In particular, in clinical populations (e.g. with cardiac pathology), HRV-based CW inference may require additional validation and possibly different analysis techniques.”

5. Line 91, p.2, the phrase 'per figure 2' is slightly ambiguous. It would be clearer to specify whether the reader should refer to Figure 2 or if there's an implied connection to the preceding text.

We restructured the statement to refer the reader to both the text and Figure 2: "The following explains in detail the different layers of the sensor, as shown in Figure 2: "

6. The separation of heart sounds is a complex task. It would be helpful to discuss whether the MCG sensor may be well-suited to address this challenge and how it might enhance the sensor's capabilities.

We have added the following discussion to Section 2.1: “One possible concern that may arise with the wearable MCG sensor is the possibility of the resulting signal being attributed to heart vibrations or sounds as opposed to MCG. However, as addressed in our previous research [18], the recorded signal is solely attributed to the heart’s magnetic field and the sensor does not measure acoustic heart sounds. Indeed, the coil design has been specifically optimized to pick up MCG signals, while the accompanying signal processing further helps suppress noise while preserving the cardiac signal."

7. It would be beneficial to clarify the inclusion criteria for participants, specifically addressing whether any participants have pre-existing cardiac conditions (e.g., heart murmurs). Such conditions could potentially affect the interpretation of heart rate variability data, particularly in waveform analysis. Specifying the participant pool would enhance the rigor of the study.

We have clarified in the revised Section 2.4 that: “Our inclusion criteria (approved by the IRB) required “healthy” status and normal BMI. No screening for subclinical conditions (like undiagnosed arrhythmias) was performed, but none of the volunteers reported any cardiovascular disease or took cardiac medications. By restricting to healthy adults, we ensured our HRV changes reflected cognitive load rather than underlying pathology.”

We have also revised Section 4 to state that: “In particular, in clinical populations (e.g. with cardiac pathology), HRV-based CW inference may require additional validation and possibly different analysis techniques.”

8. The experimental scenarios appear somewhat limited, making it difficult to demonstrate a comprehensive comparison of different workload conditions. Expanding the range of tasks and scenarios would strengthen the paper's ability to showcase the advantages of the proposed method.

Please refer to our response to comment #1 raised above.

9. I'm curious about the specific design considerations for the MCG sensor. The design, including aspects like the placement and dimensions of the conductive elements (holes, length, size), seems sophisticated. It would be interesting to see a discussion of the rationale behind the optimal design choices.

We have added the following discussion to the revised Section 2.1: "The initial optimization parameters for the coil design were previously established in [19] where the induction coil sensor was designed based on the model of a tightly winded air core coil with an inner diameter D_i, outer diameter D, length L, and wire diameter d. In this case, the sensitivity can be written as:

$$\frac{S}{D^{2.5}} = M\left(1+\frac{D_i}{D}\right)\left[\frac{1-\left(\frac{D_i}{D}\right)^5}{1-\left(\frac{D_i}{D}\right)^3}\right]^{\frac{1}{4}}\sqrt{\left(1-\left(\frac{D_i}{D}\right)^2\right)}$$

and obtains maximum values if $\frac{D_i}{D} \approx 0.6$ and $\frac{L}{D} \approx 0.7$. Therefore, by selecting a value for D, optimal values for D_i and L can be chosen.

As for the array holding these coils, the design specifications were constrained by two main criteria:

1) An array that can properly hold the coils in place, and
2) A sensor that can be properly fixed on the chest with no jittering

To address the first criterion, we 3D-printed a design with holes that are equivalent to the abovementioned length, L. By doing this, we made sure that the coils are held in place without moving. To address the second criterion, we added hooks and introduced ratchet straps so that the sensor will remain in place."

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