Longitudinal Modulation of Heart Rate Variability During Progressive Cognitive Load

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Abstract

Cortical-autonomic interactions link executive cognition and cardiovascular regulation via prefrontal-subcortical pathways. However, autonomic responses to cognitive load remain poorly explored longitudinally, specifically within-subject heart rate variability (HRV) dynamics during engagement.

Thus, this work explores longitudinal cognitive-driven HRV modulation. To this aim, 13 healthy subjects (22±3 years) were enrolled for five daily sessions, each including a first resting state, memory task (MEM), a second resting state, strategy task (STR), and a last resting state; task involved fading cues over the days. Frequency-domain and nonlinear HRV features extracted from 60-s ECG segments, followed by Friedman and Wilcoxon statistical tests.

Significant changes emerged during MEM and STR across days, while resting-state HRV remained stable, reflecting progressive task adaptation with increased vagally-mediated activity ($p<0.01$, HF and LF/HF) and altered short-term variability ($p<0.01$, $\alpha 1$).

In conclusion, these findings indicate a consistent association between autonomic modulation and cognitive engagement, with progressive autonomic differentiation tracking cognitive load, thus supporting the role of HRV for monitoring sustained cognitive effort.

1. Introduction

Cortical–autonomic interactions constitute a fundamental neurophysiological mechanism through which higher-order executive processes dynamically regulate cardiovascular function through prefrontal–subcortical pathways [1]. This bidirectional coupling is not merely supportive but essential for adaptive behavior, linking cognitive demand, emotional regulation, and physiological resilience [1, 2]. Within this framework, heart rate variability (HRV) emerges as a powerful, non-invasive biomarker, capturing the balance between sympathetic and parasympathetic influences on the sinoatrial node [1, 3].

Despite its central relevance, the temporal dynamics of this coupling, particularly under sustained or repeated cognitive demand, remain poorly understood. Existing evidence is predominantly based on single-session, cross-sectional paradigms [4, 5], which are inherently limited in their ability to capture within-subject temporal interactions or to distinguish task-specific cognitive engagement from general adaptation to repeated exposure. Consequently, a key question remains unresolved: do cardiac-derived indices, such as HRV, reflect the level and nature of cognitive processing, or do they primarily track transient, non-specific arousal responses that decrease with repeated task performance [6]?

Addressing this gap is essential for advancing neurocardiac regulation and its practical applications in cognitive neuroscience, clinical monitoring, and mental workload assessment. In this context, the present study explores a longitudinal approach to systematically investigate HRV modulation across five consecutive days, encompassing both resting conditions and cognitively demanding tasks of increasing difficulty. By characterizing how autonomic markers evolve with repeated cognitive engagement, this work aims to uncover stable versus adaptive components of brain–heart interaction, thereby providing deeper insight into the physiological signatures of sustained cognitive effort.

2. Materials & Methods

2.1. Participants

Sixteen healthy young adults were recruited in this study. Three participants were excluded due to missing or lost electrocardiographic (ECG) recordings for the day 1 resting-state segments, leaving a total of thirteen participants (22±3 years) with no history of cardiovascular, neurological, or psychiatric conditions. All participants provided written informed consent prior to enrolment, and the protocol was approved by the competent institutional ethics committee.

2.2. Experimental protocol

Each participant completed five sessions on five days: the protocol began on Wednesday and continued on Thursday and Friday, followed by a two-day break over the weekend, to be concluded on the following Monday and Tuesday (days 1 to 5).

Each session comprised five conditions in fixed order: a resting state before the memory task (RS1, 1 min, eyes closed), a memory task (MEM), a resting state between tasks (RS2, 1 min, eyes closed), a strategy task (STR), and a resting state after the strategy task (RS3, 1 min, eyes closed). In the MEM task, participants were asked to memorize the outcomes of a set of arbitrary operations (a # b = c); in the STR task, participants applied a fixed algorithm to compute the outcome of a different operation (a § b = ((b + a) − 10) + b). Both tasks followed an identical repetition (15, 18, 21, 18, and 18 trials on days 1–5, respectively) and cueing schedule across the five days, with the percentage of cued trials progressively reduced from 75% on day 1 to 50% on day 2, 25% on day 3, and 0% on days 4 and 5, enforcing a shift from cue-guided execution to memory-based retrieval. On cued trials, the equation and its result (or, for STR, the algorithm) were displayed for 3 s, followed by a 1 s blank screen; on all trials, participants then had up to 8 s to type the answer using only the right numeric pad of keyboard, followed by 3 s for feedback.

2.3. ECG acquisition and processing

Single-lead ECG signal was continuously recorded from each participant at 512 Hz throughout each session. R-peaks were detected offline using a wavelet-based ECG delineator [7]. Automatic beat correction was then applied: beats producing an RR interval below 70% of the local mean were classified as false positives and removed, while missing beats identified from RR intervals exceeding 150% of the local mean were interpolated and refined to the corresponding ECG maximum within a ±50-ms search window [8].

2.4. HRV feature extraction

For each condition (RS1, MEM, RS2, STR, RS3), HRV features were computed over 60-s ECG epochs with 30-s overlap. Tachograms derived by RR intervals were resampled at 8 Hz by using cubic-spline interpolation, and the resulting time series was mean-centered prior to spectral estimation. Power spectral density was estimated using Burg's autoregressive method, with a fixed model order of 20 and a 256-point FFT grid. Frequency-domain indices included normalized power in the low-frequency (nLF, 0.04–0.15 Hz) and high-frequency (nHF, 0.15–0.40 Hz) bands, together with the LF/HF ratio. Nonlinear dynamics were characterized using detrended fluctuation analysis (DFA), yielding short-term (α1) and long-term (α2) scaling exponents.

2.5. Statistical analysis

Longitudinal effects across the five days were assessed independently for each of the five conditions (RS1, MEM, RS2, STR, RS3) using the Friedman test. Where a significant day effect was found, Wilcoxon signed-rank tests were used for post-hoc pairwise comparisons between individual days. The significance level was set at $\alpha = 0.05$.

3. Results and Discussion

HRV features extracted during MEM tasks showed significant day-related changes for nLF ($p<0.05$), nHF ($p<0.0005$), LF/HF ($p<0.005$), α1 ($p<0.01$), and α2 ($p<0.05$), as shown in Figure 1.

Specifically, nLF and LF/HF decreased generally and progressively across days, most clearly between days 1–2 and day 4 ($p<0.01$); nHF overall increased over the same period ($p<0.01$), with day 4 higher than day 1, 2 and 3, and day 5 higher than day 1.

On the other hand, α1 decreased across days (days 4 lower than day 1-2, $p<0.01$), while α2 increased (day 4 higher than day 1, $p<0.05$). The progressive increase in nHF and decrease in LF/HF point to a progressive shift toward greater vagally-mediated modulation as the task was repeated, consistent with proceduralization of task execution and a reduced reliance on effortful prefrontal control, in line with neurovisceral integration accounts of cortical-autonomic coupling [9]. The concurrent decrease in α1 reflects a distinct dimension of this adaptation: rather than indexing sympathetic–parasympathetic balance directly, α1 captures the structural complexity of beat-to-beat correlation regulation, which emerges from the joint and integrated action of both autonomic branches [10].

Such a structure captures this adaptation more precisely than conventional frequency-domain indices alone [1]. A decline in α1 therefore may suggest reduced regulatory complexity, a shift toward a more constrained, less flexible control pattern rather than a reversal of the vagal trend seen in nHF and LF/HF. This is consistent with the proceduralization account: as MEM was repeated and cue-guided execution gave way to automatized retrieval, autonomic control itself appears to have become more streamlined, paralleling the behavioral shift from effortful, flexible engagement toward routinized performance.

During STR, significant changes emerged for nHF and LF/HF ($p<0.05$). Notably, also in this experimental condition nHF increased across days (days 4 higher than day 1–2, $p<0.05$), while LF/HF decreased (days 4 lower than day 1–3, $p<0.05$ to $p<0.01$), while α1, and α2 did not vary significantly. The direction of change is the same seen in MEM, and its emergence despite a different underlying cognitive strategy (rule-based computation rather than memory retrieval) may suggest that these autonomic markers track the level of cognitive engagement itself rather than the specific strategy employed.

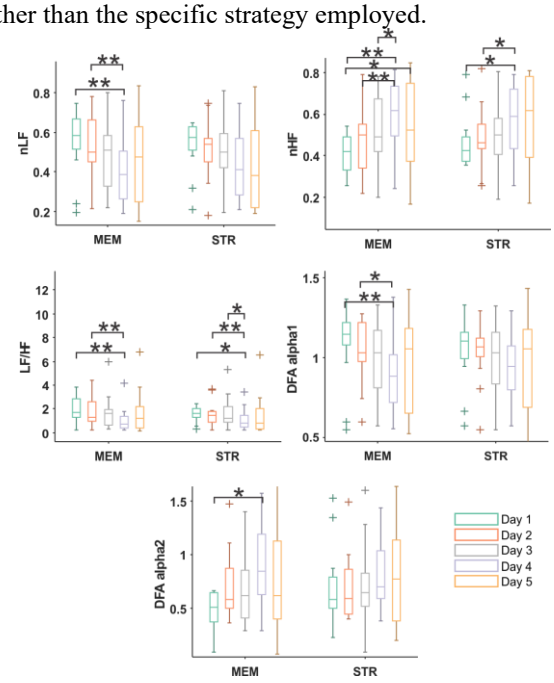

Figure 1. HRV features across days 1–5 for cognitive tasks (Memory and Strategy). *$p < 0.05$; and **$p< 0.01$

Notably, the autonomic differentiation in MEM and STR, characterized by a predominance of vagally-mediated activity in both tasks, occurred despite difficulty being progressively increased through cue removal. Therefore, this finding seems to suggest that practice-related automatization outweighed the deliberate increase in task demand. Taken together, the consistent rise in nHF power and fall in LF/HF across both cognitive tasks, set against stable resting-state HRV, support cardiac autonomic markers, as potential biomarkers of sustained cognitive effort that are sensitive to practice-related change independent of task type.

Remarkably, HRV features extracted during RS1, RS2 and RS3 showed no significant day-related variation (Friedman test, $p>0.05$ for all features), indicating a stable autonomic baseline before and after the task. This stability suggests that the autonomic adaptation observed during the MEM and STR tasks is specific to cognitive engagement rather than a general drift in baseline tone across the five-day protocol.

5. Conclusion

In this work, longitudinal cognitive-driven HRV modulation has been explored. The reported findings indicate a robust association between autonomic modulation and cognitive engagement, largely independent of task type. Progressive autonomic differentiation expressed as increasing nHF power, decreasing LF/HF ratio, and decreasing short-term DFA α1 linked to repeated cognitive engagement despite increasing task difficulty, supporting these HRV features as potential markers of sustained cognitive effort, with possible future applications in longitudinal cognitive assessment and monitoring.

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