Cognitive Load Detection Using Physiological Data from Commercial Smartwatches

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ABSTRACT
The detection and management of cognitive load has become a priority in today's technology-based world, where mental effort impacts performance and health quality. Traditional assessing methods rely on expensive and intrusive laboratory equipment, limiting the real-world applicability. This paper presents a non-invasive system for cognitive load detection using only physiological signals from commercial smartwatches. The proposed architecture includes a smartwatch application for real-time sensor data acquisition, a server for processing and storage and a web interface for visualization and control. An experimental methodology with alternating cognitive and relaxation phrases, inspired by the Pomodoro technique [1], was used to induce physiological responses. Key metrics such as heart rate (HR), heart rate variability (HRV), skin temperature, photoplethysmography (PPG) and task performance were analyzed. Results show significant HRV and HR variations between cognitive and non-cognitive phases, confirming the feasibility of wearable-based workload assessment. This work demonstrates that low-cost, accessible smartwatches can support cognitive monitoring, with using in educational, professional or health-related contexts.

Author Keywords
Cognitive Load Detection; HRV; Physiological Data; Commercial Wearables; PPG.

ACM Classification Keywords
H.5.m. Information interfaces and presentation: HCI; I.5.4. Pattern Recognition: Applications.

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INTRODUCTION
In the modern digital society, people are increasingly exposed to intense cognitive demands across educational, professional and personal contexts. Managing constant information flow and multitasking under pressure transform cognitive effort in an unavoidable routine. Monitoring cognitive load, defined as the mental effort required performing a given task, has become a focus for improving performance, supporting mental health and preventing cognitive fatigue or burnout.

Traditionally, cognitive load is assessed using specialized laboratory-based tools like EEG (Electroencephalography) or ECG (Electrocardiography). While providing high quality data, these methods are often expensive and impractical in real-world settings. To address this limitation, wearable devices are a promising alternative. Modern smartwatches integrate sensors that measure heart rate (HR), skin temperature or photoplethysmography (PPG) signals in a non-intrusive and comfortable manner.

This research investigates whether commercial wearables can reliably detect cognitive load through physiological signals. A complete system was developed using a commercially available smartwatch and consists of four components: a Kotlin-based Wear OS application for data acquisition; a Python server for communication and data management; a web interface for experiment control and data visualization; and a structured database for storage.

To validate the approach, an experimental methodology alternating between cognitive tasks and relaxation was designed. The protocol is modeled following the Pomodoro technique guidelines [1]. Participants were exposed to a standardized sequence of tasks while their physiological responses were recorded. The goal is to analyze whether significant and consistent changes are observed in the physiological data during different cognitive states.

The primary objective is to evaluate the feasibility of cognitive load detection using only commercial wearable sensors. Specific objectives include: designing a fully integrated acquisition, monitoring and processing system, implementing an experimental protocol, analyzing correlations between physiological data and mental effort, validating literature-based physiological indicators and assessing sensor reliability in cognitive load detection.

This work aims to support the development of scalable, low-cost and user-friendly tools for cognitive monitoring, with potential applications in education, workplace safety, stress management or adaptive human-computer interfaces.

RELATED WORK
Cognitive load detection is a multidisciplinary research area, involving neuroscience, computer science, psychology and biomedical engineering. The increasing complexity of

professional and educational tasks has driven efforts to measure mental load objectively and non-invasively. Studies explore a variety of methods, such as n-back, Stroop and Go/No-Go to pattern recognition or multitasking activities. Physiological data is collected using sensors such as ECG, EEG, PPG, skin temperature, HR or EDA (Electrodermal Activity). Analytical techniques range from statistical analysis (e.g., t-tests, ANOVA), time and frequency HRV (Heart-Rate Variability) metrics (e.g., RMSSD, SDNN, LF/HF), to machine learning (e.g., SVM, Random Forest) and deep learning models (e.g., CNN, LSTM).

Laboratory-grade equipment, such as multi-channel EEG, eye-tracking systems, EDA sensors and specialized ECG devices, offer high quality signals but are often costly and uncomfortable. This drives interest in evaluating the feasibility of commercial wearable sensors in cognitive load monitoring.

Howie et al. [8] investigated wearable devices in clinical tasks performed by surgeons, using HR, HRV, EDA and motion data. While correlations with cognitive load were found, the analysis relied on subjective scales (NASA-TLX) and lacked methodological accuracy.

He et al. [7] proposed a real-time cognitive load assessment system using portable EEG and HRV, achieving 97% accuracy in N-back tasks via Random Forest classifiers. Although promising, the system uses EEG, fact that complicates the real-world deployment.

Boffet et al. [3] used HRV and EDA during 2-back and emotional image tasks applying clustering and signal processing (e.g., VFCDM, WPT), to identify response profiles. Although results confirmed HF-HRV (High Frequency) and EDA as reliable markers, data acquisition required ECG and advanced, non-trivial processing.

Suzuki et al. [15], in a systematic review of workload monitoring in AR environments, noticed the utility of multimodal signals (e.g., EEG, ECG, EDA, eye-tracking, PPG) and highlighted the need for integrated systems using wearable sensors.

Barki et al. [2] introduced an ear-mounted PPG device for stress detection using deep learning (CNN and Wavelet scalograms), reaching 96% accuracy. While promising, the device was not wrist-worn and required signal augmentation and pretraining.

In conclusion, existing studies confirm the relevance of physiological signals, especially HRV and PPG, in cognitive states modeling. However, few studies implement practical systems using only commercial devices. This paper addresses this gap by developing and testing a system based entirely on wearable consumer technology, with a focus on non-invasive, simple and comfortable methods.

THEORETICAL CONCEPTS

Cognitive Load Theory and Mental Effort

Cognitive Load Theory (CLT), introduced by Sweller [16], offers a structured perspective on how individuals process information during task execution, emphasizing the limitations of working memory. According to CLT, cognitive load can be categorized into three types. The intrinsic component is determined by the complexity of the task, extraneous load is derived from how the information is presented or delivered and germane load is considered benefic and refers to the cognitive effort invested in schema construction and information integration. These types of load interact continuously during problem-solving and learning, with a direct influence on mental performance and fatigue.

Excessive cognitive load has been shown to impair executive functions such as attention and working memory, reduce information retention and lead to task errors or burnout, as mentioned by van der Linden et al. in [17]. Controlled induction of cognitive load in experimental research typically uses methods such as n-back used in [12], Stroop, Go/No-Go and dual-task tests used in [5], arithmetic operations used in [14], text reading mentioned in [11] and pattern recognition, all designed to increase mental effort in a structured manner. In this study, a hybrid protocol inspired by the Pomodoro method was employed. It alternates focused cognitive activity and relaxation periods to emulate real-world cognitive fluctuation while ensuring comparability across participants and conditions.

Wearable Sensor Technologies

Recent advancements in wearable devices have enabled the collection of physiological data with minimal intrusion and high user comfort. In this study, Samsung Galaxy Watch 5 Pro was chosen for its advanced sensor suite, developer tool compatibility and commercial availability. It supports continuous monitoring in real-world conditions and provides raw access to essential physiological parameters relevant for cognitive load assessment.

One of the critical factors in device selection was developer access to raw data. While many smartwatches offer health monitoring features, few provide APIs for low-level signals such as PPG waveforms or raw IBI (Inter-Beat Interval). This study uses Samsung Privileged Health SDK v1.2 which requires prior authorization due to its access to personal data and research capabilities.

The smartwatch integrates a variety of sensors for health tracking. Most relevant is a multi-wavelength optical PPG array (green, red, infrared) that captures volumetric blood flow changes by illuminating the skin and capturing reflected light with a photodetector. Green light is used for heart rate measurement due to its shallow penetration, while red and IR channels access deeper tissues and help reduce motion artifacts [4]. These sensors allow IBI extraction and HRV analysis without ECG.

It also features a skin temperature sensor to detect peripheral changes linked to cognitive demand. Other internal modules enable detection of sweat loss, oxygen saturation or BIA (body composition). However, these sensors require restrictive positions that limits the natural movements, so only those that allow participants to perform the tasks comfortably are used in this study.

The combination of these accessible sensors and structured API access provides a robust, non-intrusive alternative to laboratory equipment, suitable for cognitive monitoring in real world settings.

Signal Processing and Derived Parameters

To ensure accurate interpretation of physiological data, robust signal preprocessing and feature extraction were essential. Among the collected signals, HRV was prioritized as a key indicator of cognitive load due to its studied link to ANS (Autonomic Nervous System) activity. Unlike simpler metrics such as HR or skin temperature, HRV provides a deeper insight into the balance between sympathetic and parasympathetic responses to mental stress.

HRV was calculated from IBI values acquired at 1 Hz using mainly the PPG sensors. Calculations were updated every second using a 120 second sliding window, aligning with recommendations from [13] for physiological signal stabilization. Three main types of HRV analysis were used, according to [10]: time-domain, frequency-domain and nonlinear metrics.

Time-domain metrics quantify the variability directly and there are more parameters than can be derived: Mean RR, SDNN (Standard Deviation of NN Intervals), RMSSD (Root Mean Square of Successive Differences), pNN50 (Percentage of NN Intervals that Differ by More Than 50 ms) and TINN (Triangular Interpolation of NN Interval Histogram), where NN (or RR) is the time between two successive heartbeats.

Frequency-domain metrics offer insight into sympathetic-parasympathetic balance by spectral decomposition and are represented by LF (Low Frequency) power, HF (High Frequency) power and the LF/HF ratio.

Nonlinear metrics are represented by: SD1 and SD2 Poincare plots (short and long-term variability), DFA (Detrended Fluctuation Analysis) α1 and α2 for fractal complexity, Sample Entropy (SampEn) and Approximate Entropy (ApEn).

Additionally, PNS (Parasympathetic Nervous System Index) and SNS (Sympathetic Nervous System Index) indices summarize autonomic balance of parasympathetic and sympathetic components, respectively.

This processing pipeline allow the system to reliably derive real-time indicators of mental effort, enabling meaningful analysis of cognitive load using the wearable devices.

Physiological Correlates of Cognitive Load

Based on insights from literature [9] and the experimental design, several hypotheses were formulated regarding the relationship between physiological responses and cognitive load. These hypotheses guided the selection of relevant features and signal processing techniques.

For time-domain metrics of HRV, the correlations are the following:

- Mean RR is used as a general timing reference but is less sensitive to cognitive state alone.
- SDNN, RMSSD, pNN50 and TINN tend to decrease under cognitive load and increase during recovery or rest.

Frequency-domain HRV features show distinctive patterns:

- HF power, associated with parasympathetic activity, is expected to decrease during mental effort.
- LF may remain constant or show slight decrease due to its mixed sympathetic-parasympathetic origin.
- An elevated LF/HF ratio indicates increased sympathetic dominance, typical during cognitive stress.

Nonlinear HRV measures provide insight into signal complexity and autonomic flexibility:

- SD1 and SD2 decrease under cognitive load.
- DFA-α1 shows a decreasing trend in mental effort, while DFA-α2 remains relatively stable.
- Sample and Approximate Entropy both tend to decrease, reflecting reduced signal adaptability.

The PNS Index, derived from RMSSD, is lower in high-load tasks, while the SNS Index and Stress Index increase, indicating elevated sympathetic arousal.

HR is expected to increase under cognitive stress and decrease during rest, serving as a direct indicator of sympathetic activation. Skin Temperature is expected to show a slight decrease during cognitive effort, reflecting thermoregulatory responses to mental workload. PPG signals from green, red and infrared channels are monitored for amplitude changes and waveform irregularities. Variations in these signals can reflect changes in peripheral vasoconstriction, commonly associated with sympathetic activation.

These physiological markers serve as the foundation for assessing cognitive states in this experiment, allowing wearable sensor data to be interpreted in the context of mental effort.

SYSTEM ARCHITECTURE AND EXPERIMENTAL METHODOLOGY

Software Architecture and Development Tools

The conceptual architecture provides a high-level overview of the main software components and their interaction. It illustrates the structure and the data flow, without detailing specific implementation aspects. The proposed model follows a client-server architecture, where each component contributes to collect, process and store physiological data during experimental sessions.

The system includes four components: the smartwatch application, the server-side application, the web interface and the database. Each have a well-defined role and their interaction ensures the system achieves its primary objective. An overview of the architecture and inter-component communication is illustrated in Figure 1.

The smartwatch application handles the real-rime acquisition of raw physiological data from built-in sensors, including HR, IBIs, PPG (green, red, and infrared) and skin temperature. The application is implemented in Kotlin, using Android Studio, it communicates with Samsung Privileged Health SDK v1.2 and transmits the data, in real-time, to the REST API server, using the Retrofit library. Core features of the smartwatch application include user authentication and session management, connection to the Health Tracking service, periodic data acquisition, preprocessing and packaging of data, communication with the API and minimal interaction with the user through the watch interface. It uses the Observer design pattern for efficient event-driven updates when new data is available or service connectivity changes.

The server application coordinates the components of the system. It receives data from the smartwatch, validates and stores it in a structured database and facilitates data retrieval by the web interface. The server is built using Python and the Django framework, following a RESTful API architecture for standardized and scalable communication. For real-time interaction with the web interface, the server supports WebSocket communication using the ASGI (Asynchronous Server Gateway Interface) protocol. Given that the system processes personal physiological data, secure communication is enforced using JWT (JSON Web Token) authentication, embedded in the header of each API request.

The web interface serves as the primary interaction point for both researchers and participants. It guides users through the experimental protocol, displaying tasks while the smartwatch collects data in parallel. It is built using the Angular framework with TypeScript and styled with Tailwind CSS. Participants are shown their current stage in the experiment and experiment metadata is continuously sent to the backend for storage.

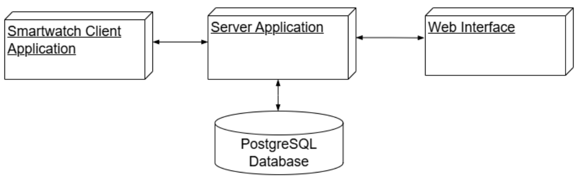

Figure 1. Conceptual architecture of the system

Beyond experiment participation, the interface also enables real-time visualization of sensor data, statistical summaries and graph-based insights.

The database ensures the persistent and organized storage of all collected data, including participant sessions, sensor measurements, task responses and timestamped events. The system uses PostgreSQL as the database engine, with a schema designed to reflect the logical flow of the experiment. The structure minimizes redundancy and supports efficient querying for downstream analysis.

Together, these components form an integrated platform for non-invasive, real-time monitoring of cognitive load using consumer-grade wearable devices, enabling both data collection and visualization in a seamless experimental workflow.

Participants and Setup

Characterizing the participant pool is essential for creating a context of the experimental results and for ensuring accurate interpretation of physiological data variations. Although the primary aim of this study was not to compare demographic groups, documenting participant profiles contributes to the transparency and reproducibility of the research.

The experiment consisted of 9 distinct data collection sessions, corresponding to a total of 8 individual participants. The distribution by gender and age category is as follows: 3 females (all within the 20-30 years age range), 5 males (4 in 30-50 years range and 1 in 20-30 years range). The age groups covered are 20-30 years (both genders) and 30-50 years (only male). To ensure participant anonymity, a simple alphanumeric identifier was used. Each subject was assigned a code consisting of the initial of their gender followed by a unique number (e.g., F1, M3). This coding system was consistently applied for linking collected data sessions with demographic attributes without disclosing personal identity.

This demographic spread, although limited in sample size, provides a reasonable basis for initial observations regarding the physiological response patterns to cognitive load within the experiment.

Experiment Structure and Protocol

To evaluate the capability of the developed system to detect changes in cognitive state based on physiological data acquired from the wearable device, an experiment was designed and implemented. The primary objective was to examine whether measurable correlations exist between physiological parameters and the mental state of the participants, categorized as either relaxation or cognitive load.

The experiment consisted of a sequence of seven consecutive tasks (alternating resting and cognitive tasks), each lasting exactly three minutes and structured as follows:

- Four relaxation tasks, intended to induce a calm physiological state with minimal cognitive activation (relax1 - video with ambient nature music, relax2 - Mandala painting video, relax3 - waterfall video and relax4 - easy puzzle activity).
- Three cognitive load tasks, aimed at engaging mental resources (cogl1 - first-sight text reading and questions answering, cogl2 - AI images classification and cogl3 - pattern recognition and sequence reproduction).

The task order was deliberately chosen to alternate between relaxation and stimulation phases, ensuring a clear physiological contrast and enhancing the visibility of signal variations between successive task states. Each task was synchronized with the experiment session and records were timestamped to ensure accurate alignment between the collected signals and the corresponding experimental stage.

The experiment aims to validate the feasibility of using a consumer-grade wearable device, such as the Samsung Galaxy Watch 5 Pro, to objectively differentiate cognitive states based only on real-time recorded physiological signals. This capability would support non-invasive, scalable cognitive state assessment in real-world scenarios, beyond controlled laboratory environments.

ANALYSIS AND RESULTS

Data Preprocessing

Physiological data was collected from the smartwatch integrated sensors at a frequency of 1 Hz and stored in a PostgreSQL database. This data was exported into session-specific Excel files containing user profiles, session and task metadata, performance metrics and detailed sensor readings (HR, IBI, PPG for all channels, and skin temperature). To ensure analytical reliability, a rigorous preprocessing pipeline was applied. This process began by validating sensor data using status flags and removing physiologically implausible values, such as IBI readings of 0 or 2048 ms (commonly resulting from SDK anomalies) or other values outside the 500-1300 ms range, in conformity with [6]. Segments with missing timestamps, zero HR readings, or data affected by noise and motion artifacts were filtered using custom rules or excluded entirely. Only complete task intervals with clean, consistent and timestamp-aligned data were retained for further analysis, ensuring high-quality inputs and preserving the integrity of physiological signal interpretation.

Statistical Analysis of Physiological Parameters

Heart rate was analyzed using two complementary methods, statistical evaluation and visual trend analysis, each offering insights into how HR responds to cognitive load.

The statistical evaluation involved calculating key metrics (e.g., mean, min, max, standard deviation) for each task across all sessions. Results showed a clear and consistent pattern that HR increased during cognitively demanding tasks and decreased during relaxation periods. Over 75% of task transitions matched this expected response, as seen in Table 1.

This result confirms HR as a robust physiological indicator of mental effort. Additionally, testing temporal offsets (15-60 seconds) to check the delayed physiological response revealed that HR reacts rapidly to cognitive shifts, with the strongest alignment at no delay or a maximum of 15 seconds delay.

The visual analysis, presented in Figure 2, based on interpolated HR signals over time, noticed how HR fluctuated across task sequences. While occasional artifacts affected signal clarity, the overall trends aligned with the statistical findings, highlighting HR elevation during cognitive load and recovery during rest.

Together, these methods confirm the heart rate sensitivity and responsiveness as an important physiological marker for tracking cognitive load using commercial wearable devices.

HRV is a sensitive physiological marker of autonomic nervous system activity and a key indicator for detecting cognitive load. This analysis explored HRV responses across experimental conditions, combining both manual and advanced signal processing.

No	Delay (s)				
	0	15	30	45	60
1	2	2	2	3	3
2	4	4	5	5	5
3	6	6	5	5	3
4	5	5	5	5	4
5	4	4	4	4	2
6	2	3	3	3	3
7	4	5	5	5	5
8	2	2	2	3	3

Table 1. Evaluation of aligned HR transitions between tasks

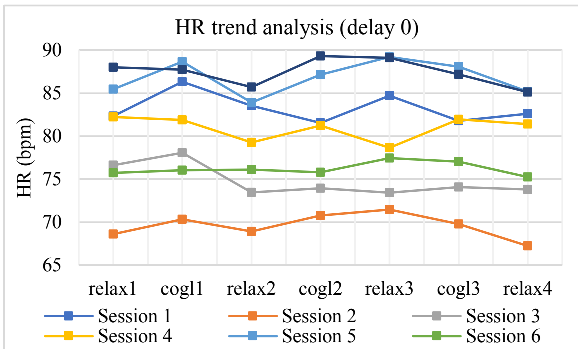

Figure 2. HR trend analysis.

No	Delay (s)				
	0	15	30	45	60
1	5	5	5	4	4
2	3	3	3	3	3
3	5	5	4	3	3
4	5	5	5	4	3
5	3	4	4	4	4
6	4	4	3	4	4
7	3	1	1	0	0
8	5	5	5	4	4

Table 3. Evaluation of aligned HRV transitions between tasks.

In the manual statistical evaluation, HRV was computed using the RMSSD formula because of the stability of the calculus. The HRV values were segmented per task and compared between relaxation and cognitive load states. Most transitions followed the theoretical pattern that HRV decreased during cognitive tasks and increased during relaxation, confirming its diagnostic relevance. This consistency was stronger without artificial delay. Applying offsets of 15-60 seconds reduced alignment, underscoring the need for time synchronized analysis. These results are summarized in Table 3.

The advanced analysis is performed using the software tool Kubios HRV Scientific Lite, version 4.1.2.1 [9]. This analysis provided a deeper examination using time-domain (RMSSD, SDNN, pNN50 and more), frequency-domain (LF, HF, LF/HF) and nonlinear parameters (SD1, SD2, ApEn, SampEn, DFA).

The sessions were analyzed in pairs to identify, in a granular manner, the trends and the behavior of physiological signals. In the first analysis, the tasks named relax1 and cogl1 were included. Subsequently, the analysis continued with the pairs relax2-cogl2 and relax3-cogl3, following the same methodological approach.

Notably, the first comparison between relax1 and cogl1 offered the strongest physiological contrasts, aligning most clearly with theoretical expectations. As the sessions progressed, the magnitude of these differences gradually decreased. While the second and third task pairs still reflected expected trends, the correlations were weaker. This progressive attenuation may reflect participant fatigue, reduced engagement or habituation to the experimental stimuli. Such effects are common in paradigms with repeated task and highlight the importance of session structure and task ordering in physiological research.

The results form Table 4 represent the mean of the three separate analyses output on the pairs of tasks:

Parameter	Relax Mean	Cognitive Mean	$\Delta_{\text{cognitiv-relax}}$
Mean HR (bpm)	78.38	79.99	1.61
RMSSD (ms)	91.49	72.48	-19.01
SDNN (ms)	77.60	62.45	-15.15
Stress Index	8.34	9.70	1.36
PNS Index	0.67	0.18	-0.48
SNS Index	0.28	0.84	0.56
pNN50 (%)	18.80	17.01	-1.80
TINN (ms)	472.71	403.13	-69.58
LF Power (ms2)	5443.50	2394.00	-3049.50
HF Power (ms2)	6952.21	2704.09	-4248.12
LF / HF	1.58	1.33	-0.25
SD1 (ms)	64.83	51.37	-13.46
SD2 (ms)	86.91	69.47	-17.44
SD2 / SD1	1.80	1.64	-0.16
ApEn	0.96	1.00	0.05
SampEn	1.40	1.50	0.10
DFA - α1	1.00	0.96	-0.04
DFA - α2	0.32	0.37	0.05

Table 4. HRV parameters resulted.

The main conclusions drawn after the analysis of every HRV metrics are:

- The mean HR was hgher in cognitive load tasks. Time-domain metrics (RMSSD, SDNN, TINN, pNN50) decreased under cognitive load, indicating reduced cardiac variability.
- Stress Index increases during cognitive load, suggesting elevated cardiac rigidity. PNS Index decreases in cognitive tasks, indicating reduced parasympathetic activity and higher mental concentration. SNS Index rises during cognitive load, confirming the sympathetic nervous system activation related to sustained attention.
- In the frequency domain, the HF and LF components decrease during cognitive load. LF/HF ratio show mixed trends, suggesting individual variability in autonomic dynamics.
- Nonlinear parameters SD1 and SD2 decline during cognitive tasks, particularly in the first two comparisons, supporting reduced complexity in heart rate patterns.
- Approximate Entropy and Sample Entropy remain relatively constant across conditions, offering limited additional insight into mental state changes.

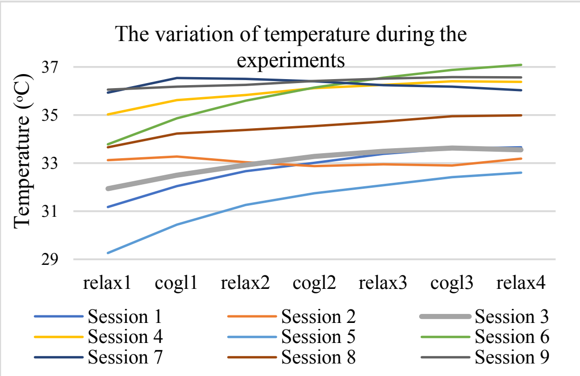

Figure 3. The analysis of temperature variations during the experiments.

- DFA-α1 and DFA-α2 remain stable, but DFA-α1 values approach to 1 during relaxation, suggesting balanced autonomic regulation in those periods [6].

Overall, HRV analysis robustly distinguished between cognitive and relaxed states, particularly through time-domain measures. The findings validate HRV as a reliable physiological marker of cognitive effort, with time-synchronized data windows yielding the most accurate results.

Skin temperature data showed a general upward trend throughout most experimental sessions, regardless of task type. While literature suggests a decrease under cognitive stress due to vasoconstriction, the short duration of each task (3 minutes) limited detection of variations. As seen in Figure 3, in 89% of sessions, the temperature increases continuously, reflecting cumulative physiological activation rather than rapid cognitive state transitions. This suggests that, while skin temperature may indicate overall stress exposure, it is less effective for short-term cognitive load detection without extended task durations or rest intervals.

PPG signals from green, red, and infrared channels were analyzed for sensitivity to cognitive load using two methods: mean amplitude and pulse peak count per task. The green channel was the most reliable, showing higher mean values during relaxation in 66.7% of sessions and more peaks in 55.6%, supporting peripheral vasoconstriction. The red channel showed increased amplitude in only 33.3% of sessions and peak analysis was unreliable. The IR channel matched the green in amplitude (66.7%) but showed inconsistent peak data. Overall, the green PPG channel provided the most stable and interpretable signal for tracking autonomic changes linked to mental effort.

Correlation Between Performance and Physiological Data

The analysis explored the relationship between the performance of participants and the consistency of physiological data, particularly HRV measures. Performance was evaluated based on correct responses from cognitive tasks, while data quality was assessed through signal continuity and alignment with literature-based physiological expectations.

The results are summarized in Figure 4. Results suggest a notable correlation between higher task performance and more stable physiological signals, especially among participants aged 30-50. In sessions where participants achieved high scores, HRV and related physiological parameters showed consistent patterns indicating a mental engagement. In contrast, younger participants (20-30 years old range) demonstrated greater variability in signal quality, even when task performance was moderate to high, likely due to reduced sustained attention or engagement.

This correlation reinforces the idea that both cognitive effort and neurophysiological maturity contribute to the reliability of physiological monitoring. Such insights emphasize the importance of participant involvement for ensuring data integrity and relevance of study.

Summary of Results

The experimental findings confirm that physiological signals collected using a commercial wearable device can reliably differentiate between cognitive load and relaxation states. HR consistently increased during cognitive tasks, while HRV parameters, particularly RMSSD, SDNN, pNN50 and TINN decreased, reflecting reduced parasympathetic activity. Frequency-domain and nonlinear HRV metrics (e.g., HF power, LF power, SD1 and SD2) also aligned with expected autonomic responses.

PPG signals showed limited utility due to signal instability (motion artifacts), with the green channel proving to be the most consistent. Skin temperature data did not reliably track short-term cognitive transitions. Performance analysis further revealed that higher cognitive engagement correlated with cleaner, more physiologically coherent data, especially among older participants. Overall, HRV metrics emerged as the most sensitive and reliable indicators for cognitive load monitoring in this experimental setup.

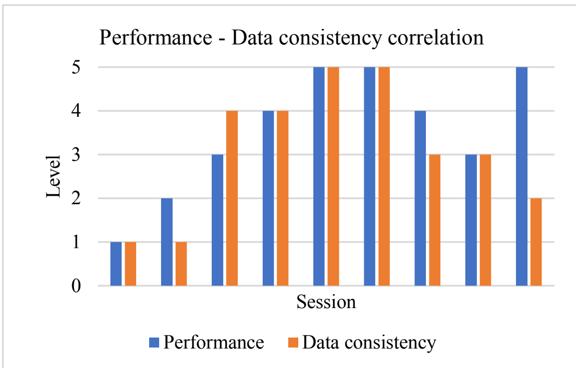

Figure 4. Correlation of performance and data consistency.

DISCUSSION AND CONCLUSIONS

This study demonstrated the feasibility of using commercial wearable devices to monitor cognitive load through physiological signals. By developing an integrated system consisting of a smartwatch app, a server backend, a web interface and a structured database, it was possible to acquire and analyze heart rate, heart rate variability, skin temperature and PPG signals during alternating periods of cognitive tasks and relaxation.

The results confirmed the hypotheses of the study and cognitive load was consistently associated with increased HR, decreased HRV (e.g., RMSSD, SDNN, pNN50, TINN), stress indices were elevated and parasympathetic activity was reduced. The green PPG channel proved to be a promising signal for analysis consistency. Frequency-domain and nonlinear metrics like DFA and Pointcare further highlighted reduced autonomic complexity under mental effort.

Despite promising outcomes, the limitations of the study, such as a small sample size, fixed task order and sensor artifacts, highlight the need for more extensive and randomized trials. Future work should focus on expanding the participant pool, refining preprocessing techniques and implementing machine learning models for real-time cognitive state classification.

Ultimately, this research supports the potential of accessible wearable technologies in real-time mental state monitoring and opens promising directions for applications in education, occupational health and cognitive performance optimization.

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