

Multimodal Cueing in Attitude Tracking Tasks: Toward the Prediction of Pilot Cognitive Workload via Physiological Measurements

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ABSTRACT

This paper investigates the relationship between variations in physiological signals, pilot performance, and mental workload during the execution of a roll-attitude compensatory tracking task. In this task, the pilot acts on the displayed error between a desired input and the comparable vehicle output motion to produce a control action. The error is displayed to the pilot using multiple cueing modalities: visual, haptic, audio, and permutations of these. In this experiment heart activity, respiration, brain activity, skin temperature, and electrodermal activity (EDA) are measured and correlated with both the participants' performance in the task, as well as with perceived mental workload through the Bedford workload questionnaire. Specific goals of the study include: (i) assessment of the perceived mental workload (MWL) for each of the cueing modalities in consideration, (ii) analysis of the relationship and correlation between performance and perceived MWL, (iii) investigation of the ability of physiological signals to distinguish different levels of MWL, and (iv) providing preliminary insights into which physiological signals are most sensitive to cognitive effort. Statistical analysis revealed that while perceived MWL is not significantly affected by multimodal cueing in good visual conditions, multimodal cueing reduces MWL in degraded/denied visual environments. Additionally, physiological responses consistently distinguished between different MWL levels across all eleven cueing modalities studied. Respiration emerged as the most statistically significant indicator, with a robust correlation with MWL variations. Conversely, EDA and skin temperature showed limited discriminatory capability in this context. The behaviors of ECG and fNIRS signals provided less consistent results and require further investigation to validate their utility in MWL assessment.

INTRODUCTION

In the context of symbiotic piloting, a human pilot shares perception and control authority with an intelligent agent to control the motion of a vehicle, acting as a symbiotic organism (Fig. 1). The term “vehicle” encompasses any machine with n-Degrees Of Freedom (DOF), capable of moving across physical space, such as airplanes, helicopters, or drones. This vehicle can either physically accommodate a human pilot or be remotely operated by one, and may have dynamics enhanced by an intelligent agent possessing human-like sensory and operational capabilities.

Presently, the perceptual models employed in symbiotic human-machine piloting primarily rely on visual (*i.e.*, sight) and vestibular (*i.e.*, equilibrium) cues, while neglecting cues like somatosensory (*e.g.*, haptic feedback) or auditory (*e.g.*, immersive 3D audio) inputs and the interactions between primary and secondary sensory channels. Consequently, there exists a knowledge gap regarding shared human-machine perception strategies for piloting vehicles within symbiotic systems operating under conditions of obstructed or impaired sensory channels (*e.g.*, degrade/denied visual environments), disrupted interactions among sensory channels, or when primary sensory inputs are supplemented with traditionally secondary perceptual cues.

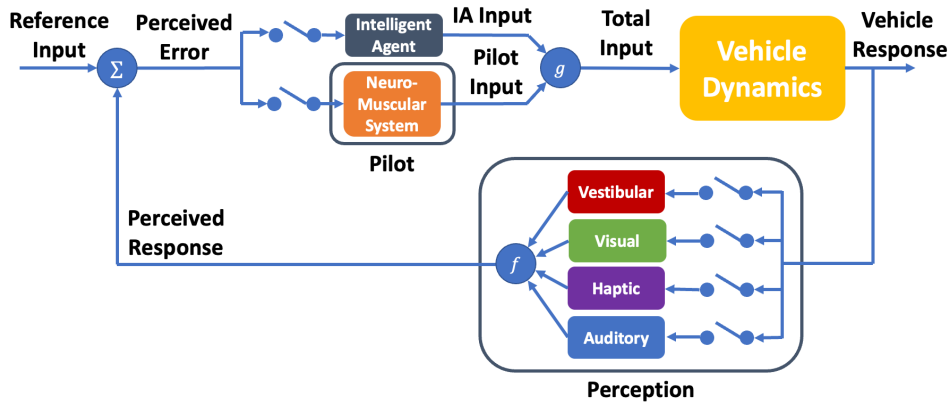


Fig. 1: Symbiotic pilot-vehicle system (PVS).

Denial or impairment of perceptual channels can come from various sources including environmental conditions (weather), limitations in machine capabilities (sensor malfunctions), or human factors such as temporary or permanent disabilities (including fatigue or high workload). In the context of flying manned aircraft, integrating secondary sensory cues into pilot models could aid in developing cueing strategies to enhance Pilot-Vehicle System (PVS) performance and mitigate spatial disorientation. Spatial disorientation is an illusion of motion that occurs when pilots are denied visual information and consequently inaccurately perceive their spatial orientation and/or direction of motion, potentially leading to catastrophic loss of control. The multi-modal cueing approach aligns with cognitive load theory, emphasizing the importance of distributing sensory information effectively across different channels to enhance task performance (Ref. 1). Moreover, leveraging information redundancy, especially when primary sensory modalities like vision are compromised, can result in multisensory augmentation. By combining sensory inputs, such as visual, haptic, and auditory cues, the overall pilot-vehicle performance can exceed that of the single cueing modalities, a concept known as the principle of *inverse effectiveness* (Refs. 2,3).

Extensive research has been dedicated to the utilization of multimodal cueing to enhance situational awareness (SA) (Refs. 4–10), pilot training (Refs. 11–19), and flight envelope protection (Refs. 20–24). Notably, haptic feedback, such as a force-feel pilot stick, has proven beneficial in pilot training by fostering motor-memory formation and aiding in specific temporal tasks. However, these studies did not explore the efficacy of full-body haptics or the combined use of haptics and spatialized audio cues to improve pilot-vehicle performance, handling qualities, and pilot modeling. In the context of somatosensory cueing, previous research has demonstrated the effectiveness of cueing the relative motion of a hovering helicopter concerning a spatially fixed target through comprehensive tactile cueing. This approach has shown promise in enhancing SA, handling qualities, and reducing pilot workload, particularly in degraded visual environments. These studies involved conveying relative linear and angular positions, velocities, and accelerations to pilots via an array of factors

using varied factor pulse patterns in terms of amplitude, frequency, and waveform to communicate pertinent information effectively (Refs. 25–28).

Recently, there has been increasing interest in full-body haptics through electrical muscular stimulation (EMS) to enhance pilot perception in and out of degraded visual environments (Ref. 29). Unlike previous approaches, these haptic cueing methods adopt a continuous rather than a binning approach. Furthermore, a subsequent investigation delved into spatial audio cueing algorithms to improve pilot perception, as referenced in another study (Ref. 30). Results from both studies consistently demonstrated enhanced or partially restored PVS performance under conditions where visual cues were compromised. These outcomes align with theories such as multisensory response enhancement and the inverse effectiveness principle within the framework of Bayesian models of multisensory integration (Refs. 31,32). Notably, feedback from test pilots revealed that varying combinations of cueing modalities influenced perceived cognitive workload. Therefore, accurately estimating mental workload (MWL) is especially important for determining optimal sensory combinations for delivering information to pilots.

The literature identifies three main methods for assessing MWL in operators: subjective questionnaires, behavioral observations, and neurophysiological assessments (Refs. 33–35). While subjective questionnaires and behavioral observations yield promising results, they have scalability and real-time applicability limitations. Conversely, neurophysiological signal analysis has shown significant potential for real-time, reliable MWL forecasting driven by advancements in the biomedical market. Signals such as cardio-respiratory activity, electrodermal activity, skin temperature, eye movements, and brain activity have demonstrated their efficacy in providing accurate, real-time assessments of pilots' MWL (Refs. 33–35).

As such, this research aims to study the relationship between variations in physiological signals, pilot performance, and mental workload during the execution of a roll attitude-tracking task (Refs. 29,30,36). In this task, the pilot acts on the displayed error between a desired input and the comparable vehicle output motion to produce a control action. The

error is displayed to the pilot using multiple cueing modalities: visual, haptic, audio, and permutations of these. In this experiment heart activity, respiration, brain activity, skin temperature, and electrodermal activity (EDA) are measured and correlated with both the participants' performance in the task, and with perceived mental workload through the Bedford workload questionnaire. The physiological signals chosen for this experiment are those (i) more closely associated with workload as per the literature (Refs. 33,37), (ii) that may be wearable in an aeronautical context, and (iii) that can be evaluated with a single acquisition system (Refs. 33,37). The specific objectives of the study are to:

1. Assess the perceived MWL for each of the cueing modalities in consideration;
2. Analyze the relationship and correlation between performance and perceived MWL;
3. Investigate the ability of physiological signals to distinguish different levels of MWL;
4. Provide preliminary insights into which physiological signals are most sensitive to cognitive effort.

This paper is structured into four additional sections. The *Materials and Methods* section delineates the characteristics of our test population and the equipment utilized, provides a comprehensive description of the roll-tracking test procedure, and details the processing of physiological signals. Following this, the *Results* section presents the strategy employed to evaluate the correlation between MWL and physiological responses. The findings from this analysis are interpreted in the subsequent *Discussion* section. Finally, the *Conclusions* section summarizes the overall findings and outlines potential future directions.

MATERIALS AND METHODS

Overview

The present study is concerned with closed-loop compensatory tracking tasks, shown in Fig. 2, wherein the pilot responds to the exhibited error e between a desired command input i and the corresponding motion output of the vehicle m to generate a control action c (Ref. 38).

Historically, pilots have been provided with information regarding the error e through visual displays, as exemplified in Figure 3. This particular display is used to cue roll and pitch attitude errors simultaneously, although for the current task only the roll attitude display is used. For pitch-axis evaluations with this display, the objective is to capture and hold the green dot within the circular bonds for each commanded pitch attitude. For roll-axis evaluations with the same display, the objective is to capture and hold the green line (*i.e.*, the roll attitude indicator m) within the bow tie bounds (*i.e.*, commanded roll attitude i) for each commanded bank angle. The

difference between the desired command input and the vehicle output motion is the error e that the pilot attempts to minimize within the defined desired and adequate performance constraints. These constraints are given by the inner and outer reticles, respectively.

In this research, the bow tie display is replaced or augmented with full-body haptic (tactile) feedback and/or spatialized spatial audio cues. Specifically, the tactile display employs localized electro-mechanical systems (EMS), where the electrodes are anatomically distributed. Headphones provide audio feedback with non-individualized head-related transfer functions (HRTFs) supplied by the slab3D software (Ref. 39). A degraded visual environment (DVE) is simulated using "fog-gles".

The goal of this analysis is to study the physiological response to different MWL levels induced during the roll-axis compensatory tracking task in each combination of sensory cueing modalities, as reported in Table 1.

Physiological Signals

The correlation between pilots' mental workload and the variations in their physiological signals has been increasingly examined with the growing accessibility of reliable and cost-effective wearable sensors. Existing literature highlights various signals that can indicate an operator's mental workload during performance (Refs. 33,37). This research employs:

- **Heart Activity:** Measured through the Electrocardiogram (ECG) signal with a triode configuration;
- **Skin Activity:** Assessed through the electrodermal activity (EDA) signal;
- **Brain Activity:** Evaluated by studying the local oxygen saturation level of the pre-frontal cortex through the functional Near-Infrared Spectroscopy (fNIRS);
- **Skin Temperature:** To evaluate the variation of peripheral temperature;
- **Respiration:** Assessed by measuring the variation of the chest volume.

The aim is to consider all signals that could be integrated into a single, wearable, and aircraft-compatible system, allowing data to be collected by one acquisition device. This approach helps avoid issues related to signal synchronization and misalignment.

Population

Fifteen healthy adults composed of 87% males and 13% females were enrolled in this study on a volunteer basis based on a power analysis according to a repeated measures, within subject design with moderate effect size, assumed correlation coefficient 0.5 and required power of 0.8 for minimum statistical significance. The age range of participants was 23 to 41,

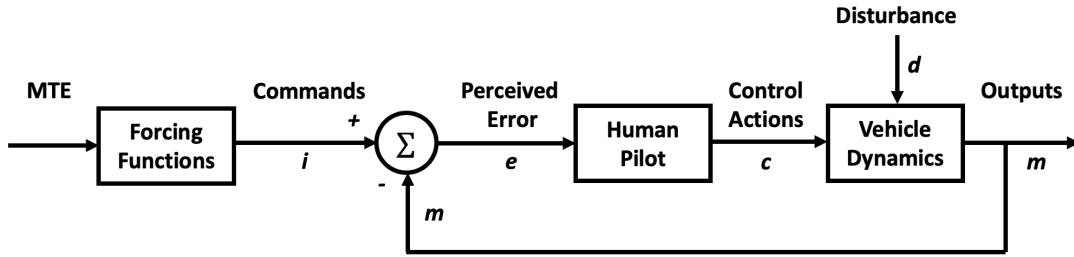


Fig. 2: Pilot vehicle system in a compensatory tracking task.

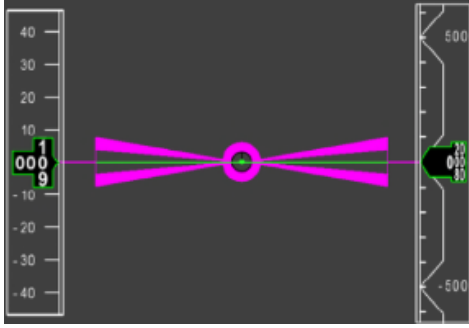


Fig. 3: Bow tie display for roll and pitch compensatory tracking tasks (reproduced from Ref. (Ref. 36)).

with a mean of 26 years. All participants had normal visual, auditory, and haptic sensitivities with no known or diagnosed history of neurological or musculoskeletal disabilities.

This experiment was carried out in accordance with the Institutional Review Board (IRB) and all measures were taken to protect the confidentiality and safety of participants. All subjects provided written consent in accordance with IRB protocol prior to participating in the experiment.

Equipment

Full-Body Haptics Full-body haptic feedback is achieved through full-body haptic suits (TESLASUITs), shown in Fig. 4a. These suits provide number of functions: (i) full-body haptics via localized electrical muscle stimulation (EMS) achieved through 80 EMS channels and 114 electrodes that can operate at frequencies of 1-150 Hz and current of 1-60 mA, (ii) biometry through heart rate (HR), arterial oxygen saturation (SpO₂), and pulse rate variability (PRV) monitoring, and (iii) full-body motion tracking through a 6/9 axes Inertial Measurement Units (IMU), and 10 internal motion capture sensors operating at a sampling rate of 100 Hz. The distribution of the electrodes on the suit is anatomically informed such that each major muscle has an electrode (Fig. 4b). EMS is controlled through frequency, amplitude, and pulse width inputs. Note that the electrode pulse width is defined as the sequence of turning the electrode on and off, which is different from the carrier frequency (*i.e.*, the frequency of the electrode when the electrode is on).

Control Inceptor A Logitech X52 Pro joystick is utilized as the pilot inceptor 5. This joystick provides three degrees of

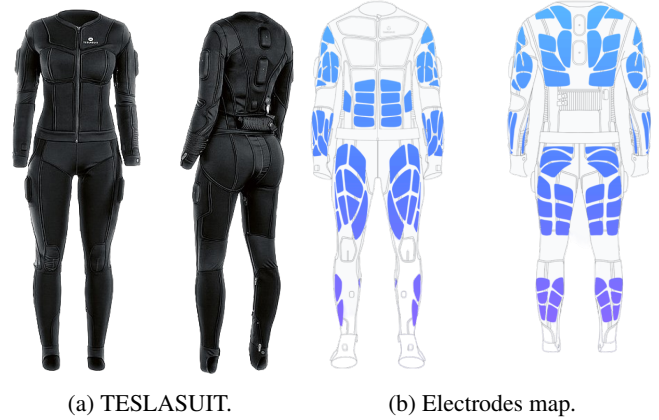


Fig. 4: Full-body haptic suit.

freedom, facilitating movement along the left/right, fore/aft, and twist axes. Additionally, the joystick is equipped with a base spring to ensure consistent stiffness.

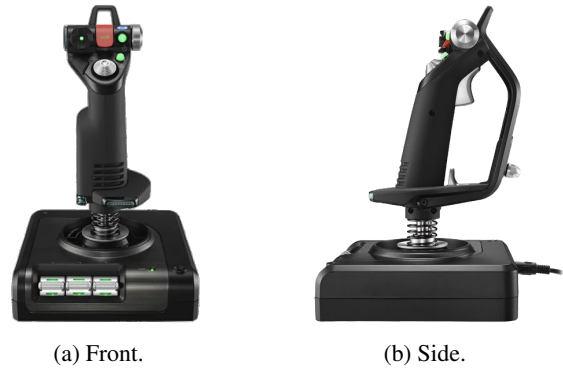


Fig. 5: Logitech X52 Pro joystick.

Spatial Audio Spatial audio cueing is achieved through the Logitech Pro-G 50 mm, a closed-ear gaming headset shown in Fig. 6. The headset guarantees good sound quality across a frequency range from 20 Hz to 20 kHz, covering the audible spectrum for human ears.

Physiological Signals Acquisition Heart activity, respiration, skin conductivity, skin temperature, and functional near-infrared spectroscopy (fNIRS) data are taken using the Biosignalsplux professional kit. This commercial and research device allows a multichannel and synchronized data stream.



Fig. 6: Logitech Pro Gaming Headset

Raw data was assessed using OpenSignals software, which allows for real-time signal acquisition and visualization, and provides raw data for the post-processing phase.

Haptic and Audio Cueing Strategy

Haptic and audio cueing strategies are based on those of (Refs. 29, 30). The general form of these strategies is a proportional-derivative (PD) compensation on the roll attitude tracking error:

$$M = K_P e_\phi + K_D \dot{e}_\phi + b \quad (1)$$

where M is a parameter representing the cued error, e_ϕ is the roll attitude tracking error, and b is a bias. The attitude tracking error is defined as the difference between the commanded and cued roll angles $e_\phi = \phi_{\text{cmd}} - \phi_{\text{dis}}$. Within the context of Fig. 1, the cued error e corresponds to e_ϕ , the desired command input i is ϕ_{cmd} and the vehicle output motion m is represented by ϕ . Note that in this compensatory tracking task $\phi_{\text{cmd}} = 0$, such that effectively $e_\phi = \phi_{\text{dis}}$. The cued bank angle is given by the difference between the actual bank attitude and some disturbance, such that $\phi_{\text{dis}} = \phi - \phi_{\text{SOS}}$. The disturbance is given by a sum of sines (SOS) signals and will be discussed later in the paper. Additionally, K_P and K_D are the proportional and derivative gains, respectively. The values adopted during the tests are reported in Table 1. The interested reader is invited to consult Refs. 29, 30 for additional detail on the haptic and audio cueing algorithms.

Test Procedure

The experiment in this study is split into two days, each day featuring a 2-hours long test session. On the first day, the participants are guided through the testing procedure, provided informed consent, and dressed with the teslasuit (with appropriate calibration) and the biosignalsplux sensors. Then, they are seated on a non-rotating chair positioned 1 meter away from a monitor displaying the task, and placed the joystick on a stool between the legs, as shown in Fig. 7. The central placement of the joystick is intended to simulate the operation of a cyclic stick in a traditional utility helicopter. Similarly, the vertical placement of the joystick is aligned to allow test subjects to rest their elbow on their thigh while using it. Once

correctly positioned, participants complete a 5-minute relaxed phase to acquire the baseline physiological signals. At the end of this phase participants complete a 2-minute trial phase to learn the task, then proceed to perform the testing blocks.

The experiment focuses on a precise, non-intrusive, roll-axis compensatory tracking task. The chosen forcing function, acting as disturbance input, consists of a sum of signs (SOS) as per Ref. 36. The SOS input is based on the Fibonacci series tailored to highlight the frequency spectrum encompassing critical vehicle dynamics and typical human pilot control actions, ranging from 0.3 to approximately 6 rad/s. The pilot's objective is to minimize displayed errors within defined performance boundaries.

This tracking task is performed for eleven different sensory cueing modalities made up of each possible combination of visual, auditory, haptic, and degraded visual feedback, as reported in Table 1. Each cueing modality is tested through five trials, each employing a distinct SOS generated with random phasing angles and stored offline. These five SOS patterns remain consistent across cueing modalities and are presented to subjects in a uniform sequence (Ref. 36). Each trial for each modality lasts 75 seconds with a brief 30 second rest period between trials. The scoring period for each trial lasts for 55 seconds, with a 10-second ramp-in/ramp-out phase at each end of the 55-second assessment window. After each modality test, a 10-level Bedford Workload questionnaire is administered to obtain a measure of subjective perceived mental workload. Following each modality, a five-minute rest phase is given to the volunteers to let the physiological signals return to their baseline. The overall duration of test trials, rest phases, and subjective questionnaire assessment, is 15 minutes; thus requiring splitting the test sessions into two days to minimize the risk of mental and physical fatigue during the tests.

Five modalities are performed on the first day and six on the second, as the preparation phase is shorter on the second day. To avoid learning biases, the order of modalities is randomized between the two days. At the start of the second day, a new 5-minute baseline assessment is conducted after partici-

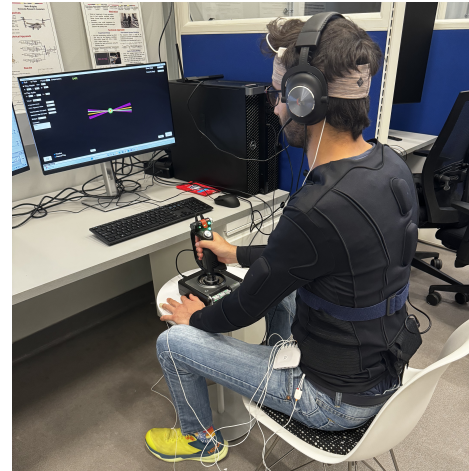


Fig. 7: Experimental setup

Table 1: Characteristics of each of the eleven test conditions performed during the multimodal cueing tests. For each modality, the name, tracking error description, audio compensator gains, and haptic compensator gains are reported (Refs. 29, 30).

Experiment #	Cueing Modality	Tracking Error Description	Audio Gains		Haptic Gains	
			K_P	K_D	K_P	K_D
1	Visual	Visual display only	-	-	-	-
2	Visual DVE	Visual display degraded by using foggles	-	-	-	-
3	Visual + Audio	Visual and stereo audio cueing	9	4	-	-
4	Visual DVE + Audio	Degraded visual display and stereo audio cueing	9	4	-	-
5	Visual + Haptic	Visual display and full-body haptic	-	-	7	5
6	Visual DVE + Haptic	Degraded visual display and full-body haptic	-	-	7	5
7	Visual + Audio + Haptic	Visual display, stereo audio, and full-body haptic	9	4	7	5
8	Visual DVE + Audio + Haptic	Degraded visual display, stereo audio, and full-body haptic	9	4	7	5
9	Audio	Stereo audio cueing	9	4	-	-
10	Haptic	Full-body haptic	-	-	7	5
11	Audio + Haptic	Stereo audio cueing and full-body haptic	9	4	7	5

pants are fitted with sensors and suits to account for any variations in their psychophysiological conditions between the two days.

The performance criteria mandate that the roll attitude tracking error remains below 5 degrees for a minimum of 50% of the scoring time for acceptable performance and under 10 degrees for at least 75% of the scoring time for optimal performance.

Aircraft Dynamics

The aircraft dynamics are chosen to be representative of the roll dynamics of a conventional utility helicopter similar to a UH-60 with Level 1 handling qualities as per ADS-33 military rotorcraft specifications (Ref. 40). The specific transfer function used in this study is:

$$Y_c(s) = \frac{\phi}{\delta_{lat}}(s) = \frac{L_{\delta_{lat}}}{s(s - L_p)} \quad (2)$$

where $L_p = -3.5$ 1/s is the roll acceleration due to the roll rate and $L_{\delta_{lat}} = 0.147$ rad/(s²·%) is the roll acceleration due to a lateral stick displacement. The SOS code and visual cueing interface of (Ref. 36) are developed in C/C++, along with an interface between these two, the spatial audio slab3D software (Ref. 39), and the aircraft dynamics. The aircraft dynamics is implemented in MATLAB®/Simulink and subsequently compiled to C/C++ code.

Physiological Signal Processing

Physiological signal processing employs state-of-the-art methodologies to extract significant features from raw time

series data collected during the tests, as outlined in (Ref. 33). Specifically, the processing algorithms for ECG, EDA, and skin temperature adopts the procedures detailed in (Refs. 37, 41), while respiration signal processing follows the methodology described in (Refs. 42, 43). fNIRS processing is conducted according to the process illustrated in (Refs. 44, 45).

Heart rate (HR) and heart rate variability (HRV) included 10 features that are extracted from both time and frequency domains. Electrodermal activity (EDA) is assessed by extracting 8 features related to its slow and fast components, namely skin conductance level (SCL) and skin conductance response (SCR), respectively. Skin temperature trends are evaluated by extracting 14 features. Respiration is analyzed to extract 18 features related to both the time and frequency content of the breath rate (BR). Finally, 38 features are extracted to assess the temporal, statistical, and frequency characteristics of the fNIRS signal. This comprehensive feature extraction resulted in a total of 88 features derived from the physiological signals in each trial of each cueing modality. Then, the five extracted values of each trial are averaged to obtain a unique feature value corresponding to the related cueing modality.

RESULTS

The goal of this research is to examine the relationship between mental workload variations and physiological signals across different cueing modalities during roll-axis compensatory tracking experiments. This section first presents the results from the subjective Bedford Workload questionnaires completed by participants at the end of each modality; then, a detailed statistical analysis between the subjective MWL results and the extracted physiological features is provided.

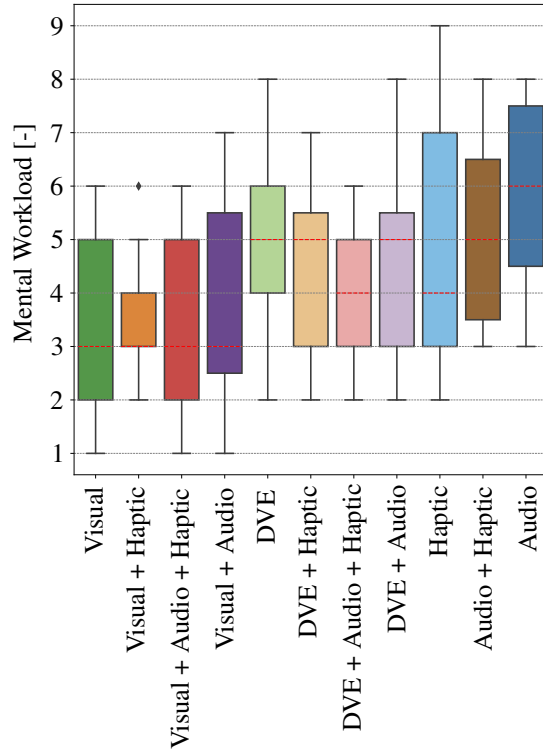


Fig. 8: Error bars related to Bedford’s MWL subjective questionnaire results for each cueing modality performed during the test. Each distribution is composed of a population of 15 people.

Bedford Scale Results

Considering the test procedure structure reported in the previous section, the Bedford Workload questionnaire is used to assess participants’ perceived MWL after each modality with an overall output n_{bedford} equal to:

$$n_{\text{bedford}} = n_{\text{mod}} \cdot n_{\text{part}} = 165 \quad (3)$$

where $n_{\text{mod}} = 11$ is the number of cueing modalities and $n_{\text{part}} = 15$ is the number of participants.

The central tendency and spread of the Bedford results are examined before analyzing the correlation of these values with the physiological data. Figure 8 shows the mean and standard deviation of the distribution of the subjective MWL rating clustered for each modality, whereas Fig. 9 displays their distribution without considering the source cueing modality of MWL’s data. The latter shows how the data gathered follows a somewhat Gaussian shape centered around a median MWL rating of 4.

Performance results

The next step in this analysis involves monitoring the volunteers’ performance during the test and examining their correlation with the perceived MWL. Two different metrics are considered for this analysis, as articulated as follows:

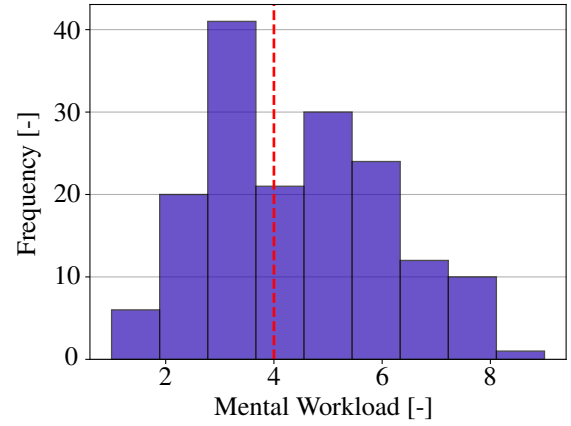


Fig. 9: Distribution of the Bedford subjective MWL outputs. The median of the distribution is reported in red and equal to 4.

1. **Roll Adequate Success Rate (RASR):** This metric requires the roll attitude tracking error to be less than 10 deg for at least 75% of the scoring time.
2. **Roll Desired Success Rate (RDSR):** This metric is defined such that the tracking error on the roll attitude is less than 5 deg for at least 50% of the scoring time.

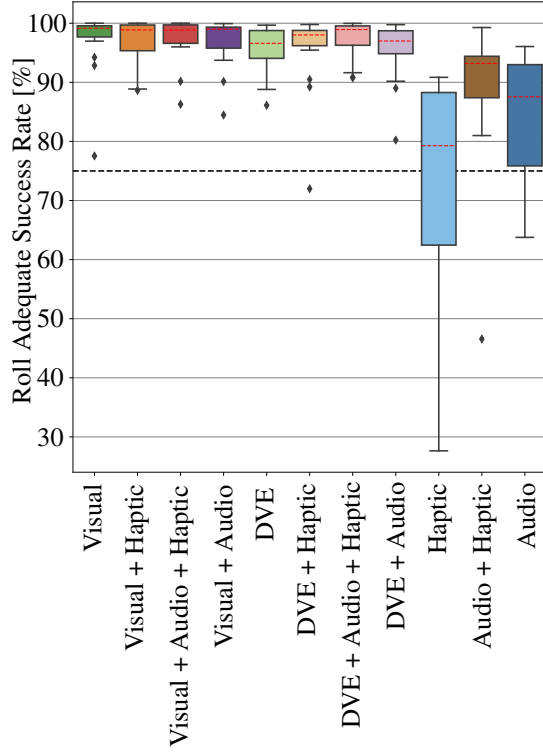
Both the RASR and RDSR are measured for each of the five trials for each participant in each modality. These five values are then averaged, resulting in fifteen performance values for each modality, corresponding to the number of participants. Hence, it was possible to report the distributions of these values, as shown in Fig. 10a and Fig. 10b.

The Pearson correlation coefficient for each modality is also evaluated to study the link between the MWL reported in Fig. 8 and the two aforementioned performance metrics. This coefficient measures the slope of the linear regression line between MWL and RASR or RDSR. A higher value indicates a stronger correlation, with 1 or -1 being the strongest and 0 indicating no correlation. A positive value (+) indicates a positive correlation, while a negative value (−) indicates a negative correlation. In our case, a negative value means that as mental workload increases, performance decreases. The results of this analysis are reported in Table 2.

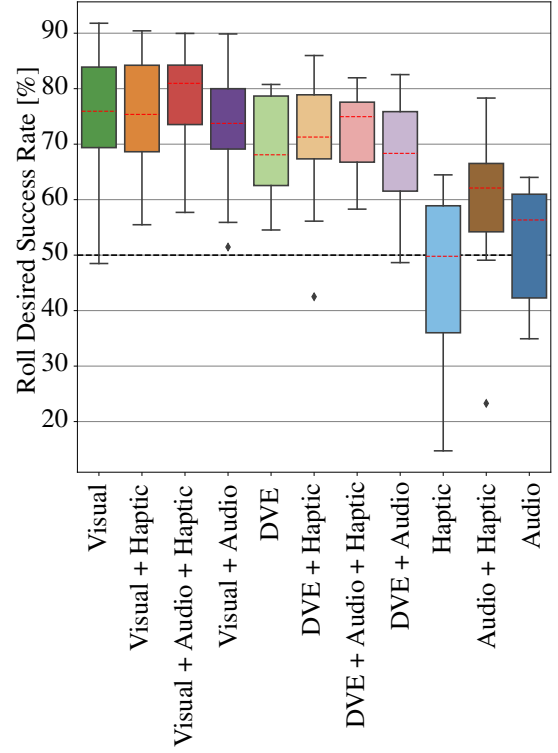
Physiological data statistical analysis

The statistical analysis of the physiological data in relation to Bedford’s MWL levels is conducted in three main steps. First, a *pre-processing* phase is undertaken to ensure a homogeneous dataset. Next, a *clustering* phase addresses the challenge of the small sample size, consisting of 15 participants. Finally, a *statistical analysis* is performed to investigate the relationship between physiological responses and perceived cognitive variations.

Pre-processing To analyze the relationship between variations in physiological signals and perceived MWL, it is essential to include baseline values of each participant. A *baseline correction* is applied to the physiological features that is



(a) RASR



(b) RDSR

Fig. 10: This figure reports for each modality the boxplots of the RADS in Fig. 10a and the RDSR in Fig. 10b.

Table 2: This table reports the Pearson’s correlation coefficients between the MWL and both RASR and RDSR for each cueing modality.

Cueing Modality	MWL - RASR	MWL - RDSR
Visual	-0.24	-0.11
Visual DVE	0.32	0.14
Visual + Audio	-0.015	-0.023
Visual DVE + Audio	0.074	0.12
Visual + Haptic	0.13	0.084
Visual DVE + Haptic	0.016	0.11
Visual + Audio + Haptic	-0.12	-0.074
Visual DVE + Audio + Haptic	0.18	0.006
Audio	-0.18	-0.28
Haptic	-0.42	-0.41
Audio + Haptic	-0.22	-0.29

computed by subtracting the mean of each feature during the baseline phase from each corresponding value during the cueing modalities. This procedure is repeated for each feature for every participant, using the two distinct baseline values from each of the test days. This method focuses on the variation of physiological features relative to their baseline values, ensuring that the baseline, when subtracted from itself, yields a value of zero for both test days. This approach mitigates the issue of differing baseline values by standardizing the data to zero for each participant. Once corrected, all data are normal-

ized using a *min-max* normalization process for each feature and participant. Therefore, each raw data point X_{raw} undergoes the following normalization process:

$$X_{norm} = \frac{(X_{raw} - X_{baseline}) - X_{min}}{X_{max} - X_{min}} \quad (4)$$

Here, X_{norm} represents the normalized value of the feature, $X_{baseline}$ denotes the corresponding baseline value, X_{min} is the minimum value of the participant’s feature after baseline correction, and X_{max} is the maximum value of the participant’s feature after baseline correction.

Upon completion of this process, the total amount of data n_{data} obtained is calculated as follows:

$$n_{data} = n_{mod} \cdot n_{part} \cdot n_f = 15840 \quad (5)$$

where $n_{mod} = 12$ is the number of modalities, including baseline conditions, and $n_f = 88$ corresponds to the number of physiological features per participant.

Clustering Each set of 88 feature values evaluated in a specific modality corresponds to a distinct Bedford MWL rating. Given the granularity of the 10-level Bedford scale compared to the dataset size, clustering is deemed necessary for robust statistical analysis. Specifically, three clusters (referred to as *Classes*) are identified and characterized as follows:

Table 3: The population distribution for each *Class* and cueing modality is reported in this table.

Cueing Modality	Class 0	Class 1	Class 2
Visual	15	10	5
Visual DVE	15	6	9
Visual + Audio	15	10	5
Visual DVE + Audio	15	7	8
Visual + Haptic	15	12	3
Visual DVE + Haptic	15	7	8
Visual + Audio + Haptic	15	10	5
Visual DVE + Audio + Haptic	15	8	7
Audio	15	4	11
Haptic	15	8	7
Audio + Haptic	15	6	9

- *Class 0* (Baseline MWL): This class represents the subset of data corresponding to the physiological baseline. It consists of 15 values for each feature, corresponding to the number of participants.
- *Class 1* (Low MWL): Comprising data associated with Bedford’s ratings lower than the median value (which is 4 based on Fig. 9), this class indicates a condition of low mental workload. It includes 88 data points for each feature.
- *Class 2* (High MWL): This cluster includes data linked to Bedford’s ratings higher than the median displayed in Fig. 9. It reflects a perception of a high mental workload and contains 77 values for each feature.

This clustering approach highlights that the distribution of data among different cueing modalities within each *Class* is not uniform, focusing rather on perceived MWL levels. Details regarding the distribution of data subsets among the classes are presented in Table 3.

Statistical analysis Following the division outlined in Table 3, an analysis is conducted to determine how many physiological features exhibited statistical significance in distinguishing the three MWL *Classes*. This analysis aims to identify features sensitive to variations in perceived MWL, thereby aiding in the evaluation of their effectiveness.

To achieve this, a statistical approach similar to that detailed in (Refs. 37, 41) is applied to the distributions within each modality *Class*. Each row from Table 3 is treated independently in a structured procedure consisting of two main steps:

1. *Kruskal-Wallis (K-W) test*: This non-parametric test is used to test for any significant differences in the medians among the three considered *Classes*. This test was chosen due to its ability to handle non-normally distributed data. A significant result ($p\text{-value}_{KW} < 0.05$, following biomedical statistical standards) indicates that at least one feature is sensitive to MWL variations, allowing further more detailed analysis.

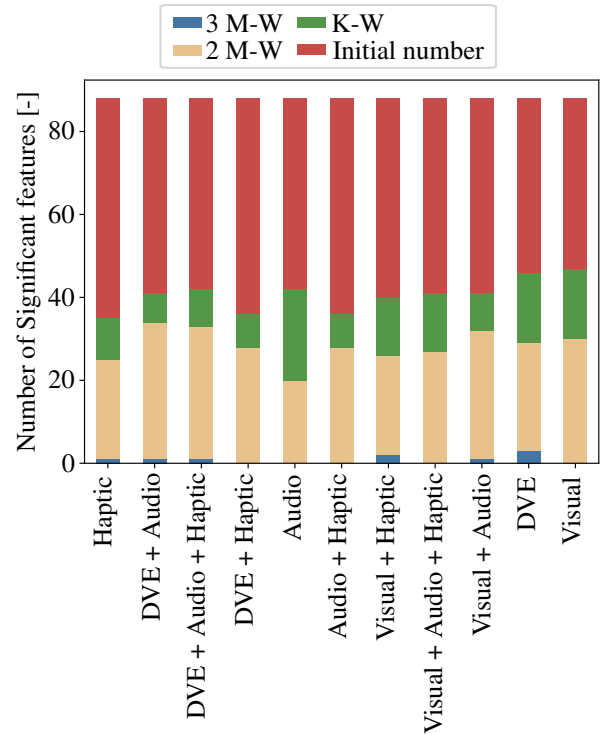


Fig. 11: This figure shows the output of the statistical analysis for each cueing modality. Blue bars indicate the number of features that demonstrated significance in three M-W comparisons. Orange bars provide relevant features in at least 2 M-W comparisons. Green bars indicate the positive output of the K-W test. Finally, red bars display the initial number of selected features.

2. *Mann-Whitney U (M-W) tests*: This test is used to compare the distributions of two independent groups. It assesses whether one group tends to have higher or lower values than the other, without assuming a normal distribution of the data. Considering the K-W’s $p\text{-value}_{KW}$ is significant, the M-W test performs pairwise comparisons between each pair of *Classes*: *Class 0* vs *Class 1*, *Class 0* vs *Class 2*, and *Class 1* vs *Class 2*. This test determines whether a feature demonstrated significant differences in distribution between these groups ($p\text{-value}_{MW} < 0.05$).

The number of features that demonstrate relevance in this statistical procedure is reported in Figure 11. This figure includes four stacked bars: the red bar represents the initial set of 88 features per modality as mentioned earlier. The green bar indicates features significant in the K-W test, while the orange and blue bars denote the number of features significant in at least 2 and all 3 M-W paired comparisons, respectively. Features significant in at least one M-W comparison are not separately depicted, as their count matches that of the K-W significant features.

Figure 12 adopts the same visual format as Fig. 11 but focuses on the results of the statistical analysis across the five involved physiological signals: ECG, EDA, Temperature (Temp), Respiration (Resp), and fNIRS, for each cueing modality. The bar heights represent the percentage (%) relative to the total

initial number of features. This approach provides detailed insights into how each physiological signal contributes to the statistical findings across different cueing modalities.

DISCUSSION

Based on the findings presented in the preceding sections, three primary observations can be made on: (i) the results obtained from the subjective Bedford Workload questionnaires (Figure 8), (ii) the overall statistical results depicted in Figure 11, and (iii) the physiological signals results shown in Figure 12:

Bedford Scale Results Consider Fig. 8. In this figure, it is shown how good visual conditions are associated with the lowest perceived MWL, whereas MWL increases as visual conditions are degraded or denied. With regards to good visual cueing, perceived MWL does not seem to vary significantly across cueing modalities (such as Visual, Visual + Haptic, *etc.*) These observations align with human’s familiarity and reliance on visual inputs for decision-making processes. Hence, incorporating additional cueing modalities in scenarios without any visual impairments does not significantly alter perceived MWL. Conversely, in degraded visual environments, there is a noticeable decrease in cognitive load with an increase in cueing modalities. For instance, the mean values of MWL distributions center around 5 for *Visual DVE* and 4 for *Visual DVE + Audio + Haptic*. This decrease in average perceived MWL rating suggests that additional cues effectively alleviate cognitive demands under conditions where visual clarity is compromised. When considering modalities excluding *Vision* or *Vision DVE*, a distinct disparity emerges between *Haptic* and *Audio* cueing. Volunteers’ subjective feedback at the conclusion of the tests highlighted that stereo system audio cues were notably precise and engaging, intensifying their focus on the mission. In contrast, feedback from the haptic suit was perceived as more challenging to interpret, likely due to lower familiarity with tactile feedback. This complexity contributed to a slight disengagement during the tests and, subsequently, lower perceived MWL levels.

Overall Statistical Results Analyzing the physiological responses shown in Figure 11, no significant differences are observed among the cueing modalities. Each condition demonstrates nearly 50% of physiological features that exhibit at least one significant difference across the three MWL *Classes*, as indicated by the K-W test results. Additionally, a notable proportion of features demonstrate statistical significance in at least 2 M-W comparisons, suggesting robust physiological responses to varying levels of perceived mental workload. However, the limited sample size of this preliminary study restricts the number of features capable of distinguishing between each paired MWL comparison.

Performance Analysis As shown in Figures 10a and 10b, multimodal cueing generally yields higher performance RASR and RDSR across the visual modalities, both in good

and degraded visual environments. In particular, multimodal cueing adopting both haptic and audio cues is shown to outperform multimodal cueing adopting a single secondary sensory modality. Additionally, multimodal cueing is shown to partially restore the performance lost due to visual cueing degradation. Lastly, cueing strategies adopting secondary sensory cues only (*i.e.*, Audio, Haptic, and Audio-Haptic modalities) yields a pronounced decrease in performance median and an increase in the variability of the distribution. These findings highlight the greater difficulty associated with non-visual tasks, a result that aligns with expectations given the reliance on vision for many cognitive processes. All of these observations are in line with Refs. (Refs. 29, 30), where the same compensatory tracking task was performed on a smaller sample size. Further supporting this trend, the correlation coefficient analysis shows a low correlation in visual conditions compared to higher correlation values in Audio, Audio-Haptic, and Haptic conditions. This suggests a more consistent relationship between different measures of performance in non-visual conditions, possibly due to the higher cognitive load and the greater variability in individual strategies for non-visual task completion. The data show how performance and mental workload do not necessarily correlate, underscoring the cognitive processes’ complexity. This highlights the need to explore MWL through alternative methodologies such as the analysis of physiological signals, as adopted in our research. These signals can provide objective and continuous measures of MWL, offering insights that are not easily captured through performance metrics alone.

Physiological Signals Results Examining the outcomes presented in Fig. 12, a consistent trend is evident across the cueing modalities. The EDA signal and body temperature display a significant number of features that do not exceed 30% in any modality condition, even when considering K-W test results. In contrast, respiration exhibits relevant results in this roll-tracking application, showing consistently high percentages of significant features for both K-W and 2 M-W comparisons. Specifically, the respiratory signal consistently maintains significant characteristics above 60% in K-W tests and reaches peaks of approximately 80% during modalities such as *Visual DVE* or *Audio*. On the other hand, fNIRS and ECG signals demonstrate intermediate trends of importance. While they exhibit a substantial number of significant features in certain modalities like *Visual + Haptic* or *Visual DVE + Audio*, in others such as *Haptic* cueing, their values are similar to those of EDA or temperature.

CONCLUSIONS

This study investigated the relationship between variations in physiological signals, pilot performance, and mental workload during the execution of a roll attitude-tracking task (Refs. 29, 30, 36). In this task, the pilot acted on the displayed error between a desired input and the comparable vehicle output motion to produce a control action. The error was displayed to the pilot using multiple cueing modalities:

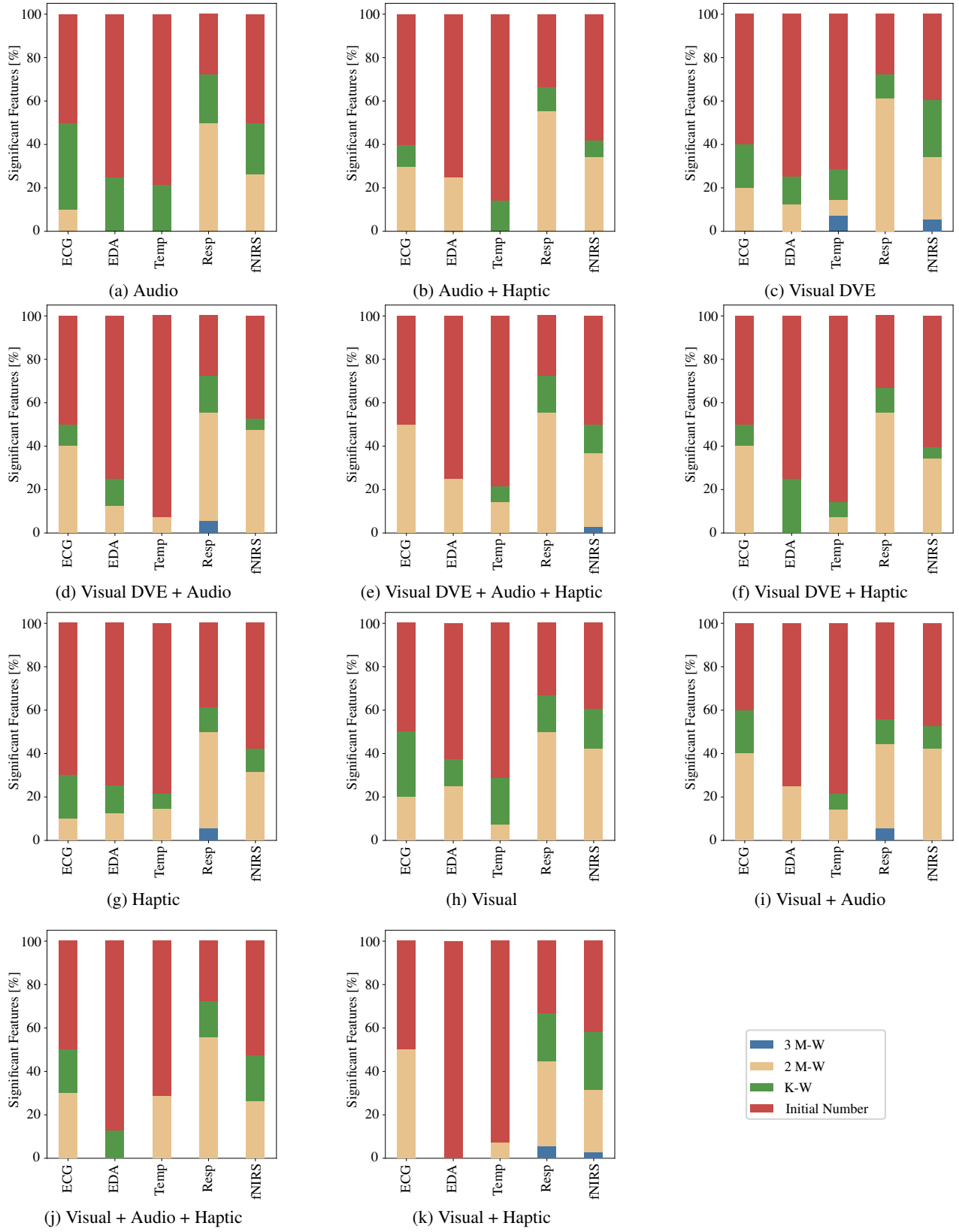


Fig. 12: This figure reports for each modality and for each physiological signal the percentage of significant features for each step of the statistical analysis.

visual, haptic, audio, and permutations of these. In this experiment five physiological such as signals—ECG, electrodermal activity (EDA), respiration, skin temperature, and functional Near-Infrared Spectroscopy (fNIRS) were measured and correlated with both the participants’ performance in the task, and with perceived mental workload (MWL) through the Bedford workload questionnaire. More specifically, the relationship between the variations in these physiological signals and cognitive load was analyzed using statistical tests including the Kruskal-Wallis and Mann-Whitney U tests. Based on this work, the following conclusions can be drawn:

1. Good visual conditions are associated with the lowest perceived MWL, whereas the perceived MWL increases as visual conditions are degraded or denied. This underscores the critical need for monitoring to mitigate potential safety risks. Interestingly, increasing the number of secondary sensory cues appears to alleviate perceived MWL in degraded/denied visual conditions, suggesting a potential strategy for enhancing cognitive load management.
2. Physiological responses consistently distinguished between different MWL levels across all eleven cueing modalities studied. Respiration emerged as the most statistically significant indicator, with a robust correlation with MWL variations. Conversely, EDA and skin temperature showed limited discriminatory capability in this context. The behaviors of ECG and fNIRS signals provided less consistent results and require further investigation to validate their utility in MWL assessment. In particular, it will be crucial to explore whether the observed differences in feature significance across modalities derive from inherent application diversity or are specific to this preliminary investigation stage.
3. The correlation coefficient analysis between pilot performance and physiological markers shows a low correlation for visual cueing modalities and higher correlation values for non-visual cueing (*i.e.*, Audio, Audio-Haptic, and Haptic modalities). This suggests a more consistent relationship between different measures of performance in non-visual conditions, possibly due to the higher cognitive load and the greater variability in individual strategies for non-visual task completion. The data show how performance and mental workload do not necessarily correlate, underscoring the cognitive processes’ complexity.

These findings highlight the importance of multimodal cueing in managing MWL and underscore the need for continued investigation into physiological markers for accurate MWL assessment. Future research should involve expanding the study population to develop a robust dataset for training an Artificial Intelligence (AI) classification algorithm capable of real-time cognitive load prediction in pilots under multimodal cueing conditions. This advancement has the potential to enhance the development of safer, high-performance pilot-vehicle systems.

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