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Stress Resilience Assessment Based on Physiological Features in Selection of Air Traffic Controllers

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ABSTRACT Stress resilience is recognized as an important occupational prerequisite for air traffic controllers (ATCs). A system for input/output multimodal stress resilience assessment based on physiological features has been developed and applied in the ATC selection process on 40 ATC candidates, as well as on 40 age/sex-matched control subjects. The input stimulation paradigm includes acoustic startle stimuli and their prepulse and fear-potentiated modulations, airblasts, and semantically relevant aversive images and sounds. The output physiological features include resting heart rate variability and respiratory sinus arrhythmia, cardiac allostasis, electromyogram- and electrodermal activity-based acoustic startle response features, like startle reactivity and startle habituation, and acoustic startle modulation-related features, like fear-potentiated startle, prepulse inhibition of the startle response, and discrimination of startle responses in danger versus safety experimental conditions. Variability of each feature is assessed and illustrated in 8-D physiological resilience space. Statistically significant differences ($p < 0.05$) between the two groups have been obtained for the three most relevant of eight applied features; specifically, ATC candidates exhibited significantly higher resting respiratory sinus arrhythmia, lower startle reactivity, and more pronounced cardiac allostasis than the control group. The observed feature variability justifies future research efforts toward augmenting the traditional ATC selection process with the presented stress resilience assessment approach. The proposed research paradigm can be also applied in selection processes of similarly stressful occupations such as first responders, airline/military pilots, military personnel, among others.

INDEX TERMS Stress resilience assessment, air traffic controller, startle stimuli, heart rate variability, respiratory sinus arrhythmia.

I. INTRODUCTION

Air Traffic Controller (ATC) is a highly demanding and stressful occupation that relies on high levels of complex cognitive performance and individual psychological resilience. Potential risks of losing human lives, high workloads and heavy time pressures all contribute to ATCs high-stress occupational environment [1] that can cause long-lasting mental health, neurobehavioral, immune and operational decrements in low-resilient individuals [2]–[5]. Prolonged occupational exposure to such environments can cause fatal operational errors in inadequately selected, trained, and resilient individuals. Furthermore, a job analysis of ATCs [6] revealed high importance of adjustment, self-control, stress tolerance, and adaptability/flexibility in ATC occupation, all of which are related to resilient functioning under stress. Therefore, stress resilience [7], [8] should be one of the most important criteria during ATC selection process.

The most important sources of operational stressors for ATCs are high peaks of traffic load, time pressure, a variety of emergencies, conflicts in the application of rules, the potential failure of equipment, shift schedules-night work, lack of

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sleep etc. [3], [9]. These stress-eliciting factors, as well as overlapping fatigue factors like workload, shift length, break frequency, circadian rhythms, sleep disorders etc. [10], can affect the job satisfaction and the general health of ATCs. This can lead, in case of cognitive overload and time pressure, to a loss of situational awareness [11]. Information intensive work environments, traffic jams, multitasking activities, rapidly changing workload, lack of sleep, fatigue, and other factors may cause long-lasting neurobehavioral decrements or even severe mental health disorders [3]. Idiosyncratic factors such as age, biological, genetic and personality traits, lifestyle, work experience, motivation, physical and mental health, etc. contribute to the complex aetiology of these stress-related health disorders. Exposure to high levels of stress also impairs the performance of tasks that require complex cognitive abilities and flexible thinking [12], as well as precision [13], but it can improve the performance of simpler and/or well-rehearsed tasks [14], [15]. Early detection and prevention of stress-related neurobehavioral decrements remain challenging due to substantial individual differences in resilience and the associated psychophysiological factors.

Even though stress has long been recognized as an inherent part of the ATC profession [16], [17], a review of contemporary literature [18] emphasizes that stress in ATC has been neglected by researchers in comparison with other human factors like situational awareness [19], [20] and workload [21]–[26]. While there is no direct method to assess resilience to stress, there are a number of psychometric instruments that measure constructs related to stress resilience, such as scales of hardiness, locus of control, optimism, self-efficacy, as well as a variety of comprehensive physiological measurements [27]–[29] that can be used to create a comprehensive psychophysiological stress response profile.

Different indicators of peripheral physiological activity, such as cardiovascular, electrodermal, and electromyographic activity, have long been used as indicators of primary emotions [30], [31] and conscious manipulation of these signals is much harder than speech or facial emotional expressions [32]. From these signals a wide range of physiological features can be computed through time/frequency analysis, entropy, geometric analysis, sub-band spectra, multi scale entropy domains, or various decomposition methods. Finding the dominant set of physiological features, that are the most relevant for differentiating resilient from vulnerable individuals, has been a main objective of our research [33]–[40]. These research results are used to augment and objectivize the ATC selection process.

This article proposes methodology for stress resilience assessment based on comprehensive physiological features in the selection of ATCs. Accordingly, multimodal physiological measurements were conducted with the group of 40 candidates in the final stages of the ATC selection process and age/sex-matched control group of our 40 students. Between-group comparative analysis is presented for eight physiological features for stress resilience assessment according to the relevant references given in Table 1 in the next section. The main contribution of the paper is the proposed methodology for elicitation and computation of selected physiological features, which is empirically evaluated based on features that statistically differentiate experimental and control group.

II. BACKGROUND OF PHYSIOLOGICAL FEATURES FOR STRESS RESILIENCE ASSESSMENT

This section summarises the background research publications regarding physiological features of stress resilience, which represents the scientific basis for our research in this paper. Table 1 presents the relevant research findings and structures these findings according to specific physiological features of stress resilience that we have identified in the scientific literature: root mean square of successive differences (RMSSD), respiratory sinus arrhythmia (RSA), cardiac allostasis (CA), startle reactivity (SR), startle habituation (SH), prepulse inhibition (PPI), fear-potentiated startle (FPS) and danger vs. safety discrimination (DSD). Accordingly, these features are used in scientifically grounded stress resilience assessments conducted with our two groups of participants in the subsequent sections of this paper. Prospective studies of stress resilience, which are regarded as particularly valuable in stress resilience research [41], [42], are highlighted in the table by asterisks.

III. METHODS

Design and development of comprehensive methods for ATC candidates' selection should reflect the full spectrum of realistic occupational operational demands and relevant stimuli for stress resilience assessment. Low-cost wearable micro-sensors for measurements of the individual's multimodal physiological, acoustic, linguistic, facial, oculomotor, functional near-infrared spectroscopy (fNIRS) and EEG reactions [35], [64] have the potential to be used in the selection of resilient ATCs. Accordingly, the laboratory version of Input/Output Multimodal System for Stress Resilience Assessment (IOMS-SRA) enables measurements and analysis of multimodal responses to specific stressful stimuli, related to physiological, facial, acoustic, linguistic, oculomotor and electroencephalographic (EEG) features [34], [36], [37], [65]. This approach is illustrated by Fig. 1.

A. STUDY PARTICIPANTS

This research complied with the American Psychological Association Code of Ethics and had been approved by the Croatian Air Traffic Control authorities and the Ethical Committee of the University of Zagreb Faculty of Electrical Engineering and Computing. Signed informed consent was obtained from each individual participating in this research. The Croatian Air Traffic Control selected 40 individuals for participation in our experimental procedures from the pool of more than one thousand applicants, according to: educational level and age; cognitive, perceptual and physical abilities, vocational/avocational interests, personality traits

TABLE 1. Summary of physiological features relevant for stress resilience assessment.

Physiological Feature and Brief Description	Relevant Research Findings	Research References	Conclusion
Root mean square of successive differences (RMSSD) – measures rapid heartbeat-to-heartbeat variability, which is considered to reflect cardiac parasympathetic activity [43]	Resting vagally-mediated heart rate variability (HRV) (assessed via RMSSD) was negatively associated with depressive symptoms both 13 and 34 months later (measured by the Center for Epidemiological Studies Depression Scale), in university students/employees.	*[44]	Higher RMSSD should indicate higher resilience to stress.
	Resting vagal control (measured by RMSSD during the 5-min baseline) showed positive association with trait resilience (measured by the Ego-Resiliency Scale) in peacekeepers.	[45]	
	Low resting RMSSD was associated with impaired post-stress recovery of cardiovascular, endocrine, and immune markers in healthy males.	[47]	
Respiratory sinus arrhythmia (RSA) – measures a phenomenon characterised by heart rate fluctuations that are in phase with inhalation and exhalation [46]	Nearly all reviewed studies that addressed the link between RSA and resilience are represented by cross-sectional investigations, which quite consistently support the view that RSA is reduced in PTSD sufferers.	[28]	Higher RSA should indicate higher resilience to stress.
Cardiac allostasis (CA) – measures adaptive reaction to a stressful event, which involves a vigorous cardiac response to stress coupled with significant cardiac recovery in the aftermath [45]	Resilience measured by the Ego-Resiliency Scale correlated positively with cardiac parameters for both stress reactivity and recovery in peacekeepers.	[45]	Higher cardiac allostasis should indicate higher resilience to stress.
	In post-stress recovery period, the student participants with higher resilience significantly reduced stress-induced tachycardia.	[48]	
Startle reactivity (SR) – measures the strength of reflexive defensive responding to an aversive unconditioned stimulus, i.e., abrupt, loud noise [49]	Baseline pre-deployment startle magnitude was significantly greater in active duty Marines who went on to develop PTSD symptoms after deployment.	*[50]	Lower startle reactivity should indicate higher resilience to stress.
	Individual differences in general startle reactivity, measured via orbicularis oculi EMG, may index premorbid vulnerability for psychopathology.	[49]	
	Greater general startle reflex in orbicularis oculi EMG was associated with greater state anxiety levels measured by the State-Trait Anxiety Inventory, in a sample of female students.	[51]	
	Higher startle response amplitude in orbicularis oculi EMG distinguished nonclinical subjects with self-reported negativity bias, compared to those with positivity bias.	[52]	
	Reviewed results suggest that general startle reactivity appears to be elevated in PTSD.	[53]	
Startle habituation (SH) – measures reduced responding over repeated presentations of startle stimuli [54]	Slower skin conductance habituation to startling sounds prospectively predicted more severe PTSD symptoms following one year of exposure to police-related trauma.	*[54]	Stronger / faster / steeper startle habituation should indicate higher resilience to stress.
	Significant negative correlation was obtained between skin conductance habituation slopes to acoustic startle probes and resilience scores of healthy adults, measured via self-report scales.	[55]	
	Slower absolute habituation of skin conductance response magnitude to startling tones was shown in the current and lifetime PTSD groups compared with the never PTSD group.	[56]	
	PTSD patients had impaired orbicularis oculi EMG habituation to acoustic startle probes in comparison with control group of war veterans.	[57]	
Prepulse inhibition (PPI) – measures the ability of a weak prepulse to reduce the startle response to a subsequent startle-eliciting stimulus [60]	High prepulse inhibition was associated with increased resilience to develop PTSD after deployment in active duty Marines.	*[58]	Stronger / enhanced prepulse inhibition should indicate higher resilience to stress.
	Enhanced prepulse inhibition with 120 ms lead intervals, measured via orbicularis oculi EMG, predicted better treatment response in chronic PTSD patients.	*[59]	
	Prepulse inhibition of eyeblink EMG startle response was reduced in the PTSD veterans, compared to the non-PTSD civilians.	[60]	
Fear-potentiated startle (FPS) – measures the enhancement of the startle reflex during exposure to aversive, threatening, or fear-inducing stimulus cues [62]	Greater skin conductance responses to startling sounds under high threat of electric shock prospectively predicted more severe PTSD symptoms following one year of exposure to police-related trauma.	*[54]	Lower fear-potentiated startle should indicate higher resilience to stress.
	Greater eyeblink EMG and skin conductance responses to startling sounds in the medium threat-of-shock condition were related to greater PTSD symptom severity in police officers.	[61]	
	The magnitude of eyeblink EMG startle response was increased throughout the threat-of-shock experiment in the PTSD veterans vs. non-PTSD controls.	[60]	
	Significant positive association in a sample of undergraduates was found between eyeblink EMG startle potentiation during aversive picture viewing and a fear index computed via a battery of self-report scales.	[62]	
Danger vs. safety discrimination (DSD) – measures differential startle responding during exposure to danger cues vs. exposure to safety cues [63]	Reduced safety signal learning at pre-deployment was found in active duty Marines who went on to develop PTSD post-deployment, compared to those who did not.	*[58]	Higher danger vs. safety discrimination should indicate higher resilience to stress.
	Patients with a PTSD diagnosis, unlike controls, did not demonstrate discrimination between danger and safety cues, assessed via orbicularis oculi EMG startle responses in conditioned danger and conditioned safety contexts.	[63]	

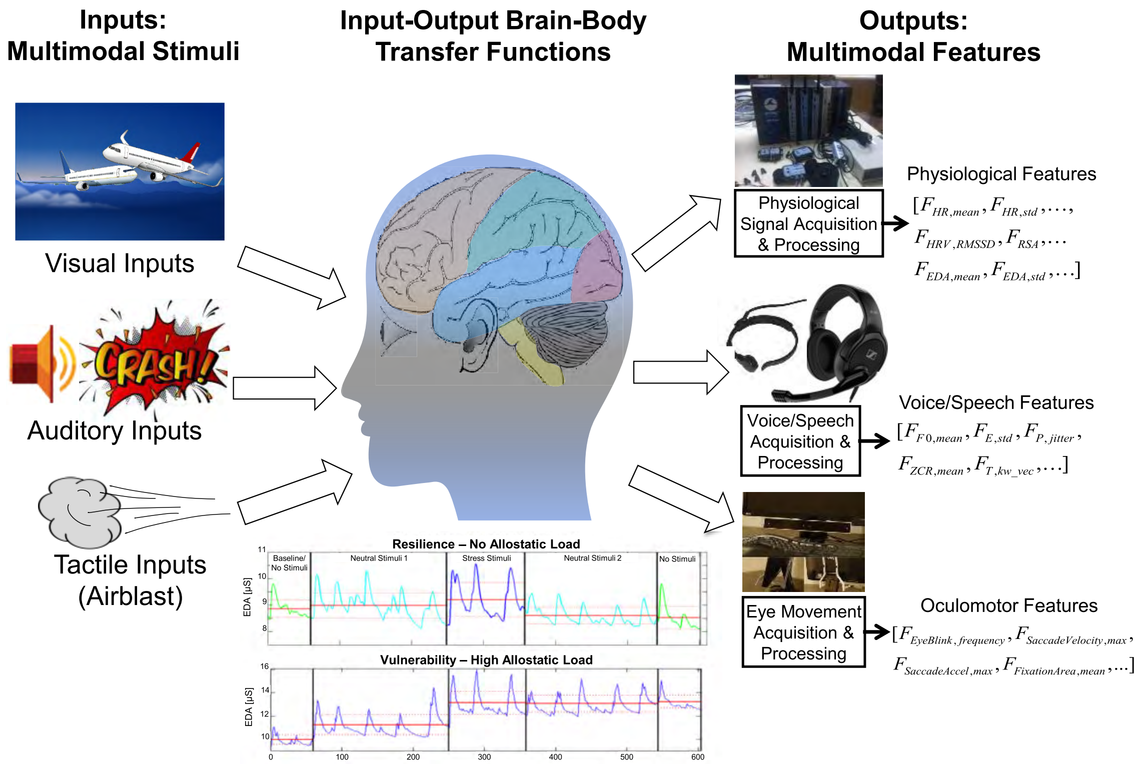

FIGURE 1. The laboratory version of IOMS-SRA (presented illustration was partially assembled from public domain/free sources: https://publicdomainvectors.org, http://www.stockunlimited.com).

and behavioural tendencies; First European Air Traffic Controller Selection Test (FEAST) and Dynamic Air Traffic Controller Radar Test (DART), developed and managed by EUROCONTROL (http://feast-info.eurocontrol.int/); psychological interview regarding abilities to handle the ATC occupational demands; performance on simulated exercises related to air traffic management etc. At the beginning of our protocol, each ATC candidate filled out several standardised psychological questionnaires relevant for resilience assessment: Connor-Davidson Resilience Scale [66], Anxiety Sensitivity Index [67] and Core Self-Evaluations Scale [68]. Later on, candidates underwent proposed stimulation paradigm while their peripheral physiology was continuously recorded, including ECG, EDA, respiration, and eyeblink EMG signals. Due to psychological questionnaires' susceptibility to bias [28] and potentially fake self-report results caused by candidates competing for attractive job and salary, this research was mainly focused on comprehensive multimodal physiological measurements and analysis as the primary tools in the objectivization of stress resilience assessment. The control group participants were 40 5^{th}-year electrical engineering and computing students. These participants underwent the same experimental protocol as ATC candidates.

The actual number of ATC candidates and control participants whose data are presented in this paper were 38 ATC candidates (33 male, 5 female, median age 24) and 36 control participants (30 male, 6 female, median age 23.5), respectively. Specifically, data from 2 ATC candidates had to be excluded from the analysis due to data recording fault. Data from 4 control group participants had to be excluded from the analysis for the following reasons: 1 participant reported an anxiety disorder; 1 participant could not finish the experiment due to high levels of discomfort; and, 2 participants were excluded due to data recording fault.

Wilcoxon-Mann-Whitney two-sample rank-sum test showed no significant difference between these two groups in age ($\text{median}_{\text{ATC}} = 24$, $\text{median}_{\text{CTRL}} = 23.5$, ranksum $= 1390$, $p = 0.6632$, effect size $r = 0.05$). Fisher's exact text showed no significant difference between the two groups in male/female composition ($p = 0.7510$, $OR = 0.7576$).

B. STIMULATION PARADIGM

Both groups underwent the same stimulation paradigm, with controlled lighting and temperature in the room. The stimulation paradigm for stress resilience assessment has been designed to elicit physiological response features summarised in Table 1, and included the following blocks:

- **Resting block**. This block lasts 3 minutes and is primarily used for computation of resting cardiac activity features (HRV and respiratory sinus arrhythmia).
- **Block of auditory startle (AS) stimuli**. This 2-minute block of 8 white-noise AS stimuli (duration 40 ms, loudness 108 dB, according to [63], [69]) is particularly important for computation of electromyographic

(EMG)- and electrodermal activity (EDA)-based measures of the AS response habituation.

- **Block of prepulse inhibition of AS**. This 3-minute block contains 4 referent (pulse-alone) AS stimuli and 8 prepulse-inhibited AS stimuli, mixed in pseudorandom order. Prepulse-inhibited AS stimuli are preceded by 25-ms acoustic prepulses (75 dB, 1000 Hz, 4 ms rise/fall times) with 120-ms lead intervals [59].
- **Block of fear-potentiated AS stimuli**. This 5-minute block is divided into 4 phases, where the candidates are alternately confronted either with words "danger", written in red, or words for "no danger", written in blue, on a screen in front of them. Throughout the "danger" and "no danger" phases, typical acoustic 40-ms 108-dB white-noise startle stimuli are delivered (8 under instructed danger, and 8 under instructed safety, in total), for assessment of the fear-potentiated startle response and danger vs. safety discrimination. Besides the AS stimuli, 4 unpleasant composite stimuli (2 in each of the 2 "danger" phases), are delivered as well. Composite stimuli are combinations of aversive 250-ms airblasts, loud unpleasant sounds and aversive pictures [37], and cause a relatively strong cardiac and EDA response. Hence, ECG data from this block (specifically the "danger" phases) is used for the assessment of cardiac reaction to laboratory stress, as part of cardiac allostatic response analysis.
- **Recovery block**. This block lasts 2 minutes and is important for the coupled analysis of cardiac reaction (from the previous block) and cardiac recovery from laboratory stress.

In all blocks, intervals between successive stimuli were 15±2 seconds.

Fig. 2 shows a schematic view of the stimulation paradigm timeline that was used in our experiment. AS stimuli and sound components of the composite stimuli were delivered binaurally through headphones (Sennheiser PC 360 G4ME). Airblasts were directed at the back of the neck. Visual components of the composite stimuli and "danger"/"no danger" instructions were presented on a screen that was black otherwise. Just before their enrolment in the experiment, an experimenter verbally explained the study procedures to each participant.

C. DATA COLLECTION PROCEDURES

BIOPAC MP150 system with all accompanying modality-specific modules was used for collecting the ECG, EMG, EDA and respiratory data, at a sampling frequency of 1000 Hz. Gazepoint GP3 HD eye-tracker was used for spontaneous blink detection, collecting data at a frequency of 150 Hz. Synchronisation of the stimulus delivery and data acquisition hardware was performed by our IOMS-SRA software. A more detailed description of the hardware side of our laboratory system can be found in [37].

The eyeblink component of the AS response was measured by EMG recordings of the right *orbicularis oculi* muscle with two disposable electrodes (EL504 from BIOPAC) precoated with electrolyte gel. One electrode was positioned right below the eye, and the other was positioned below the lateral canthus. The electrodes were considered successfully placed when the eyeblink EMG response contour was clearly distinguishable from the baseline EMG activity during real-time raw data visualization. ECG electrodes (EL503 from BIOPAC) were placed on both wrists and above the right ankle (Einthoven's triangle) and Lead I was measured. EDA was measured as conductance between the two isotonic gel electrodes (EL507 from BIOPAC) placed on the index and ring finger of the nondominant hand. Respiration was measured by respiratory belt placed around the participant's chest (approx. at the height of the diaphragm). The electrodes were considered successfully placed if QRS complexes in the ECG and SCRs in the skin conductance signals were easily visible. Visual inspection of signals after electrode placement, lasting one minute, additionally helped the participants' signals to settle to a basal rest level before the start of the paradigm.

D. DATA PROCESSING AND ANALYSIS PROCEDURES

ECG was processed using a highly robust automatic heartbeat detection algorithm [70] and a MATLAB-based tool for manual checking and correction of detected heartbeats, resulting with an inter-beat interval (IBI) time series on a 1-ms precision scale. Such highly precise detection of heartbeats was critical for accurate assessment of the fluctuations in the obtained IBI time series, known as heart rate variability (HRV). In general, changes in HRV have been shown to relate to stress [71], as well as anxiety, depression, PTSD, fatigue etc., all of which produce autonomic imbalance [72]. While an array of time-domain, frequency-domain and nonlinear measures can be generally used to assess HRV [71], [72], we focused on HRV assessment via RMSSD and RSA features due to resilience-relevant literature presented in Table 1.

AS response magnitudes were quantified using both the EMG and EDA data. The eyeblink EMG startle response magnitude was measured via peak amplitude of response in the accordingly preprocessed EMG signal, in line with the recommendations from [73]. Specifically, the raw EMG signal was preprocessed by a high-order FIR band-pass filter (28–500 Hz), rectified, smoothed using a 10 Hz low-pass filter, and baseline-corrected. All startle responses were manually checked and excluded from the analysis if there were any artifacts or high levels of noise present in the signal at the time of AS probe delivery. The EDA-based startle measure was integral (area under curve) of the sudomotor nerve activity (SMNA) response, calculated on a time window of 6 seconds after delivery of AS stimulus. The SMNA signal (or the EDA driver signal) was estimated from filtered EDA data using a state-of-the-art EDA processing approach cvxEDA [74], and is interpreted as sympathetic activity estimate.

From the processed physiological signals, the 8 selected features (Table 1) were computed for each ATC candidate and

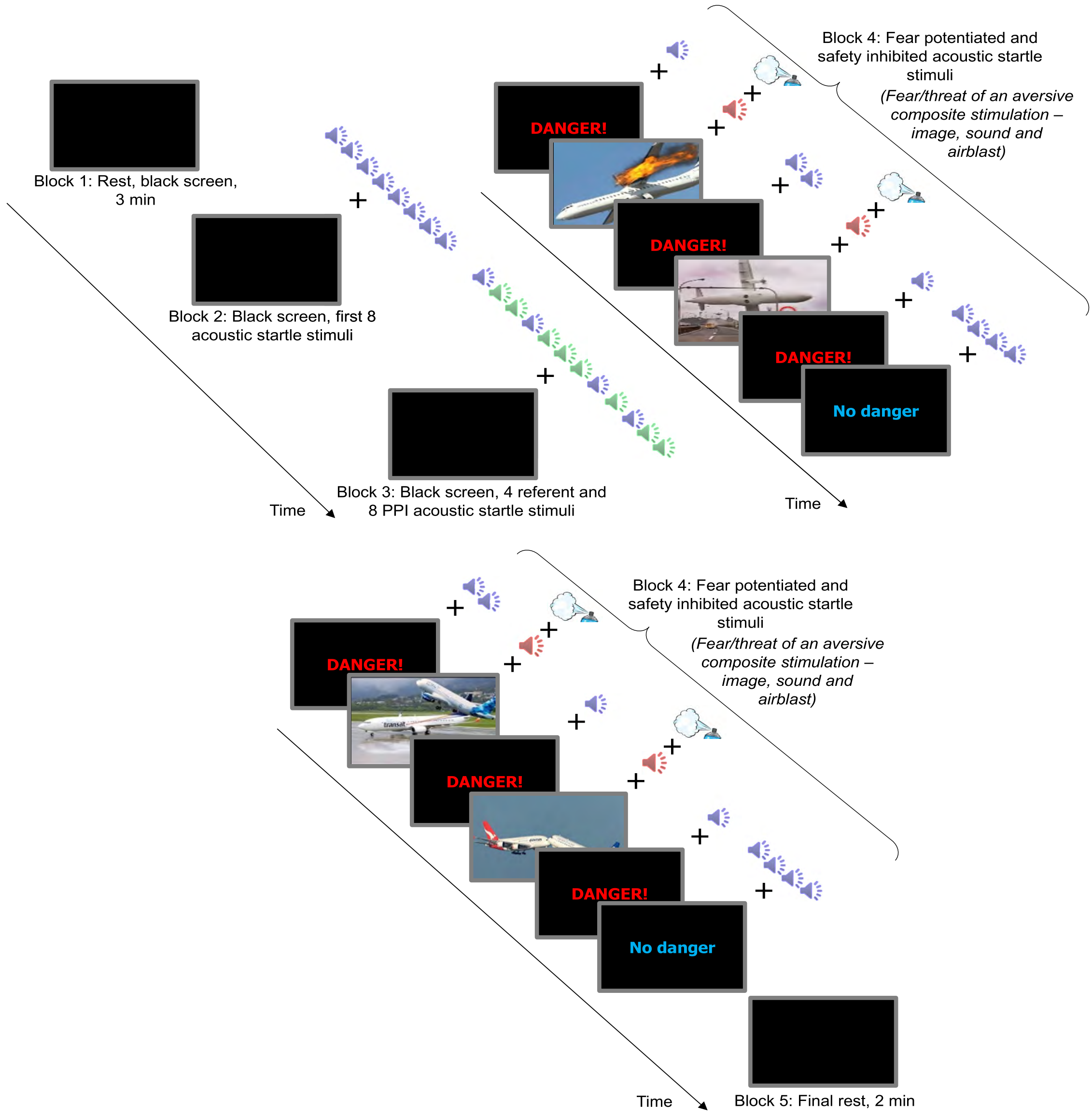

FIGURE 2. A schematic overview of the stimulation paradigm that was used in the experiment.

each control group participant. Description of computation methods for each feature is given immediately before the presentation of the corresponding results in the following section.

All statistical analyses were performed in MATLAB R2017b. Between-group comparisons of each of the 8 selected features were performed by Wilcoxon-Mann-Whitney two-sample rank-sum tests, and the differences were considered significant when $p < 0.05$. In order to check that various startle conditions used in the stimulation paradigm show expected amplifications/attenuations of AS responses across all participants, one-sample t-tests were used.

IV. RESULTS

A. HEART RATE (HR) RELATED FEATURES

RMSSD and RSA features were calculated from the respiratory and ECG data collected during the first 3 minutes of the paradigm (resting period), what is comparable with recommended minimal window durations for resting HRV assessment [75]. Cardiac allostasis feature was calculated by analysis of cardiac stress reaction and recovery conducted over relevant segments of ECG data.

Root Mean Square of the Successive Differences (RMSSD) is very sensitive to high-frequency oscillations in the cardiac IBI signal, so even rare occurrences of heartbeats that might not be of sine node origin, or ectopic beats, can induce high levels of noise in the RMSSD feature, and masquerade as vagally-mediated HRV [72]. To address the problem, we have implemented a robust version of the RMSSD feature that rejects outliers in the IBI successive differences series through a semi-automatic procedure that is based on percentile thresholding and manual inspection. Such removal of ectopic beats before RMSSD computation is in line with recommendations in [76]. Fig. 3 shows boxplot

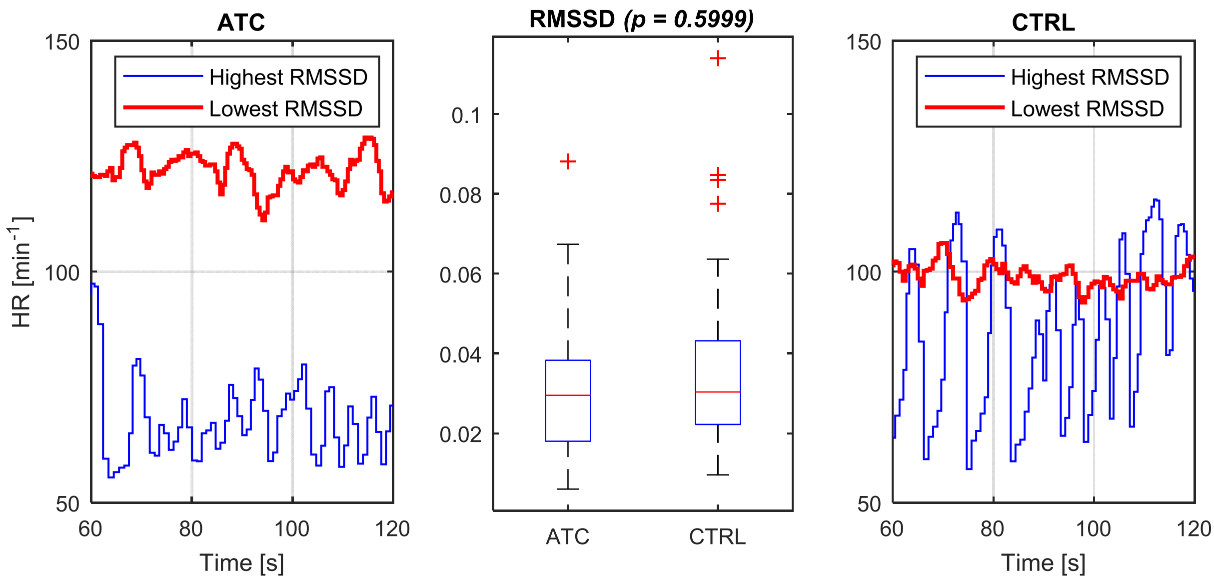

FIGURE 3. Boxplot of RMSSD feature during the 3 minutes of rest for ATC candidates vs. control group (middle); illustration of ATC candidate with the lowest and highest RMSSD (left); illustration of control group participant with the lowest and highest RMSSD (right).

of RMSSD feature for ATC candidates vs. control group, as well as illustrations of two most distinct ATC candidates and control group participants concerning RMSSD. Higher RMSSD values should indicate higher resilience according to Table 1. Wilcoxon-Mann-Whitney two-sample rank-sum test shows no significant difference between the two groups ($\text{median}_{ATC} = 0.0304$, $\text{median}_{CTRL} = 0.0302$, ranksum = 1376, p = 0.5999, effect size r = −0.06).

Respiratory Sinus Arrhythmia (RSA) assessment usually includes simple measures like the high-frequency HRV [77] (ignoring respiratory activity) or descriptive statistics such as range (peak-to-trough differences in IBI times determined on a breath-by-breath basis). Methodological issues of RSA assessment have thus been a field of extensive discussion and research in the past years [46], [78]–[80]. In our work, similarly to [80], we have integrated 4 different RSA estimation methods that are methodologically motivated by the definition of RSA in the context of signal processing—coupling between respiratory effort and cardiac rhythm [81].

The 4 resulting RSA-related features that are obtained from the processed ECG and respiratory data acquired during the first 3 minutes of rest are:

- Mean peak-to-trough difference in IBI times determined on a breath-by-breath basis. For each respiratory cycle, we determine the difference between the longest IBI interval during expiration and shortest IBI interval during inspiration.
- Correlation between uniformly resampled (10Hz) baseline-corrected IBI time series and respiratory effort signal in the time domain (Spearman's correlation coefficient was used). The phase shift between the two signals is estimated via cross-correlation and taken into account.
- Relative HRV power spectral density (PSD) estimate around the breathing frequency (±0.015Hz). The breathing frequency is assessed via a maximum value in the PSD estimate of the respiratory effort signal. HRV PSD estimation was done using the Lomb-Scargle periodogram, as recently suggested by [82], without resampling.
- Correlation between the uniformly resampled HRV PSD estimate and respiratory PSD estimate (Spearman's correlation coefficient was used).

These 4 methods combined provide a relatively robust and complete description of the cardiac-respiratory coupling referred to as respiratory sinus arrhythmia. A final measure of RSA for each participant/candidate is the linear combination of the 4 differently calculated RSA features that corresponds to the first PCA axis. The first PCA axis explains 67.45% of the total variance in the 4 RSA-related features.

Fig. 4 shows boxplot of RSA feature for ATC candidates vs. control group, as well as illustrations of two most distinct ATC candidates and control group participants concerning RSA. Higher RSA values should indicate higher resilience according to Table 1. Wilcoxon-Mann-Whitney two-sample rank-sum test shows significant difference between the two groups ($\text{median}_{ATC} = 0.3570$, $\text{median}_{CTRL} = -0.0481$, ranksum = 1632, p = 0.0255, effect size r = 0.26). Furthermore, values of RSA feature in ATC group are overall higher than in the control group, as demonstrated by the respective distributions depicted in the boxplot.

Cardiac Allostasis (CA) is considered to represent vigorous cardiac reaction, coupled by successful recovery after laboratory stress. Similarly to [45], we measured cardiac reaction by the reduction in mean IBI time, and RMSSD, from baseline to "danger", and cardiac recovery by the increase in mean IBI and RMSSD, from "danger" to

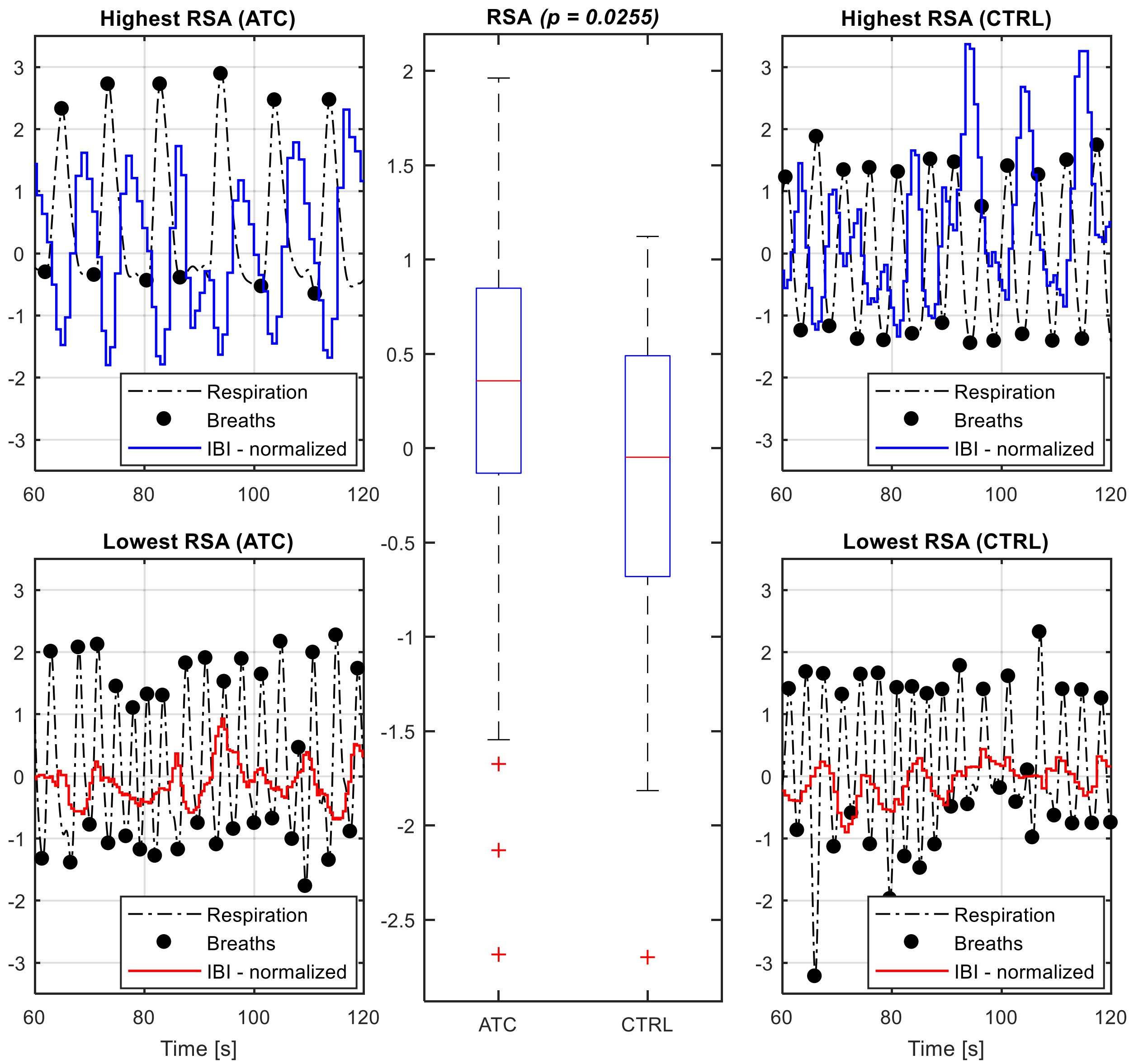

FIGURE 4. **Boxplot of RSA feature during the 3 minutes of rest for ATC candidates vs. control group (middle); illustration of ATC candidate with the lowest and highest RSA (left); illustration of control group participant with the lowest and highest RSA (right).**

recovery, on 1-minute long segments. The baseline values of IBI and RMSSD are calculated from 3 1-minute long segments during rest, reaction values of IBI and RMSSD are calculated from 2 1-minute long "danger" segments, and recovery values of IBI and RMSSD are calculated from 2 1-minute long recovery segments before the end of the paradigm [81]. The main cause of laboratory stress in "danger" phases is the context of danger/fear coupled with exposure to highly aversive composite stimuli. Fig. 5 shows boxplot of CA feature for ATC candidates vs. control group, as well as illustrations of two most distinct ATC candidates and control group participants concerning CA. Higher CA values should indicate higher resilience according to Table 1. Wilcoxon-Mann-Whitney two-sample rank-sum test shows significant difference between the two groups ($\text{median}_{\text{ATC}} = 0.0176$, $\text{median}_{\text{CTRL}} = -0.5903$, ranksum = 1669, p = 0.008, effect size r = 0.31). Furthermore, values of CA feature in ATC group are overall higher than in the control group, as demonstrated by the respective distributions depicted in the boxplot.

B. AS RESPONSE RELATED FEATURES

Based on the quantified AS responses, the following features are calculated:

Startle Reactivity (SR) is assessed by averaging a certain number of eyeblink EMG startle responses that are first presented to the candidate, as a part of the baseline procedure [49], [51]. In this paper, the first 4 AS stimuli for the assessment of SR have been used, as we believe that this is enough to reduce the measurement noise, but still not enough for the measure to become very susceptible to the effects of

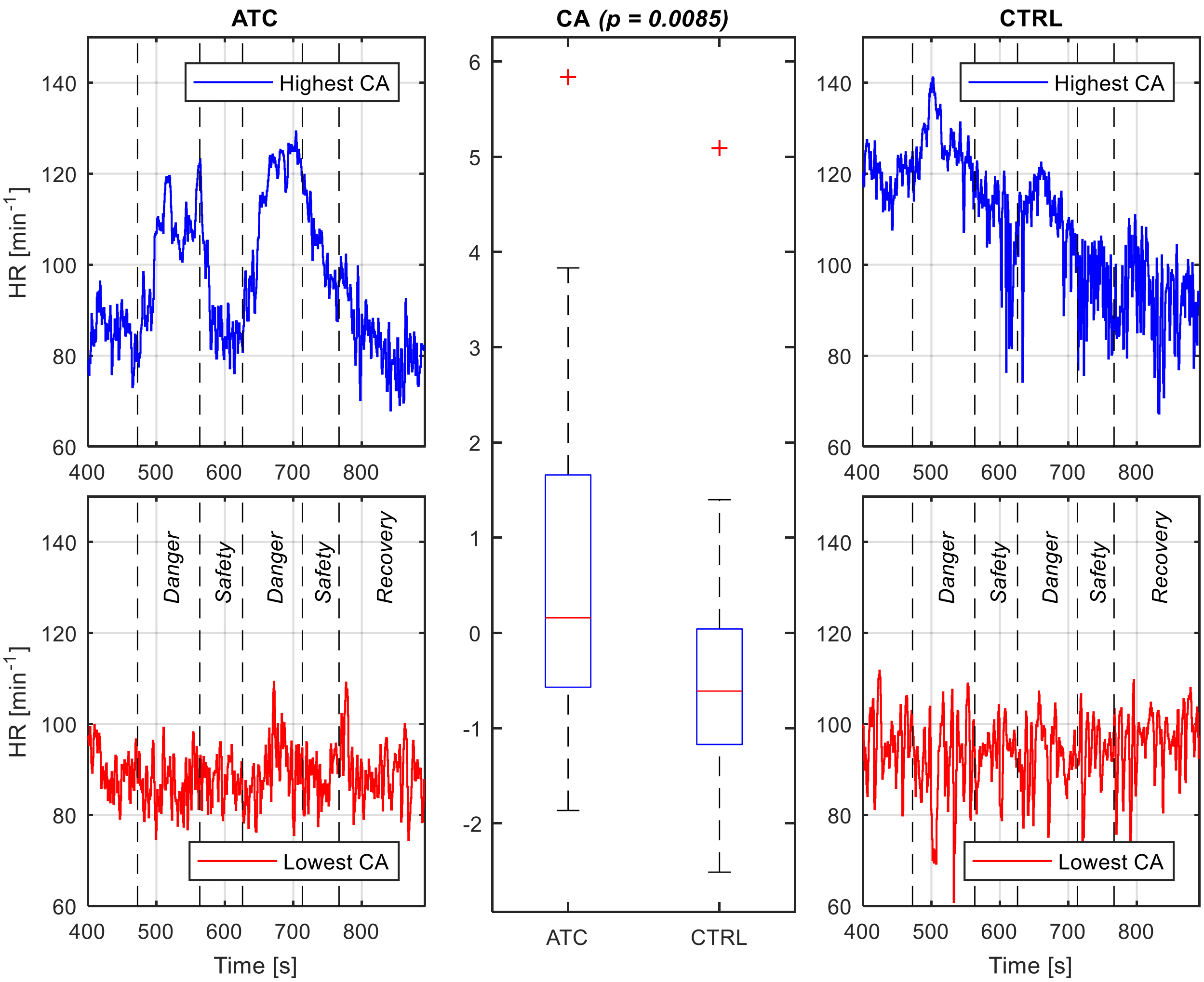

FIGURE 5. Boxplot of CA feature for ATC candidates vs. control group (middle); instantaneous HR signals of ATC candidate with the highest and lowest CA (left); instantaneous HR signals of control group participant with the highest and lowest CA (right).

startle habituation as well. SR is normalised by amplitudes of EMG responses preceding the spontaneous blinks during the first 3 minutes of rest phase. Fig. 6 shows the boxplot of SR feature for ATC candidates vs. control group, as well as illustrations of two most distinct ATC candidates and control group participants concerning SR. Lower SR values should indicate higher resilience according to Table 1. Wilcoxon-Mann-Whitney two-sample rank-sum test shows significant difference between the two groups ($\text{median}_{\text{ATC}} = 0.8437$, $\text{median}_{\text{CTRL}} = 1.4802$, ranksum $= 1217$, $p = 0.0248$, effect size $r = -0.26$). Furthermore, values of SR feature in ATC group are overall lower than in the control group, as demonstrated by the respective distributions depicted in the boxplot.

Startle Habituation (SH) is estimated from the first 8 AS response measurements, in both EMG and EDA modalities. It is known that habituation can in some individuals be preceded by a short period of sensitisation [83], and the effect was observed in our data sample as well. Therefore, we employ 3 different measures of habituation, that together provide a more robust estimate of habituation than a single one [81]. Fig. 7 shows boxplot of SH feature for ATC candidates vs. control group, as well as illustrations of two most distinct ATC candidates and control group participants concerning SH. Lower values of SH estimate computed in the described way mean stronger habituation, which should indicate higher resilience according to Table 1. Wilcoxon-Mann-Whitney two-sample rank-sum test shows no significant difference between the two groups ($\text{median}_{\text{ATC}} = 0.0901$, $\text{median}_{\text{CTRL}} = -0.2163$, ranksum $= 1580$, $p = 0.0947$, effect size $r = 0.19$).

The aim in analysing the startle modulation features was to quantify the effects of different startle modulation conditions on magnitude change in the AS response. Prepulse inhibition and safety conditions tend to inhibit the response, while danger condition tends to potentiate the response. The 3 startle modulation features are calculated for both modalities, EMG and EDA, in the following way:

- **Prepulse Inhibition (PPI)**is the average startle reflex magnitude for 8 prepulse inhibited AS stimuli, divided by the average startle reflex magnitude for 8 referent

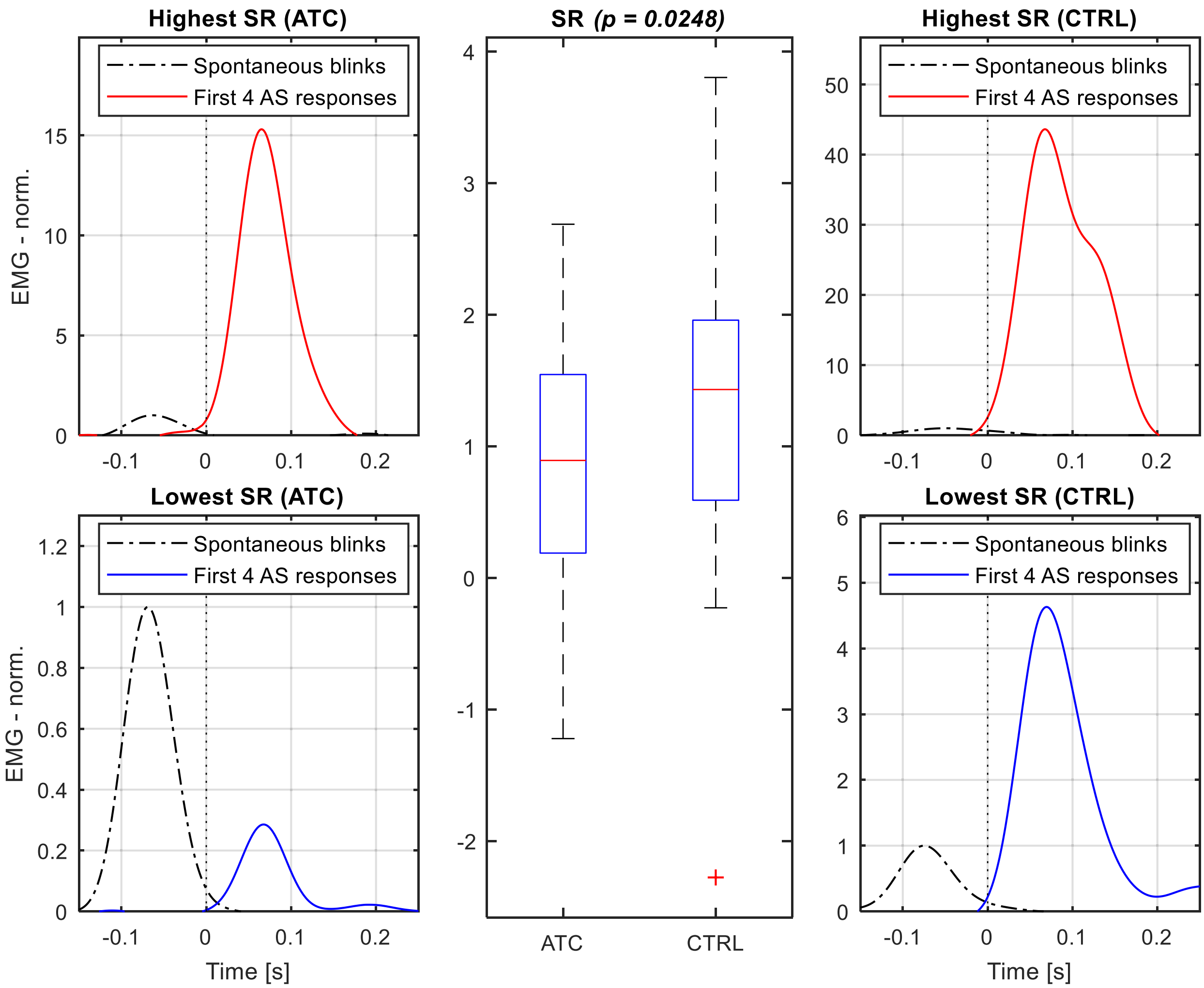

FIGURE 6. Boxplot of SR feature for ATC candidates vs. control group (middle); illustration of ATC candidate with the highest and lowest SR (left); illustration of control group participant with the highest and lowest SR (right). Value of 1 on y-axis in each illustration corresponds to the average eyeblink EMG amplitude for the specific candidate, calculated from spontaneous blinks during rest. Time 0 corresponds to the startle stimulus onset in AS response graph and to the eye-closed moment in graph of spontaneous blinks.

AS stimuli (last 4 AS stimuli from the habituation block, and 4 pulse-alone AS stimuli from the PPI block). Lower PPI values computed in the described way mean stronger prepulse inhibition, which should indicate higher resilience according to Table 1.

- **Fear-Potentiated Startle (FPS)** is the average startle reflex magnitude for 8 fear-potentiated AS stimuli, divided by the average startle reflex magnitude for 8 referent AS stimuli (same as in PPI). Lower FPS values should indicate higher resilience according to Table 1.
- **Danger vs. Safety Discrimination (DSD)** is the average startle reflex magnitude for 8 fear-potentiated AS stimuli, divided by the average startle reflex magnitude for 8 AS stimuli delivered during the two "safety" blocks. Higher DSD values should indicate higher resilience according to Table 1.

The described approaches to computation of startle modulation features result in a total of 6 features (3 EMG-based and 3 EDA-based features). Final features that are used as modality-independent measures of PPI, FPS and DSD are obtained from factor analysis, identifying the loading estimates of the 3 factors that underly the EMG- and EDA-based PPI, FPS and DSD features [81]. This approach is, to the best of our knowledge, the first attempt of calculating modality-independent estimates of these psychophysiological resilience-related AS-modulation-based phenomena.

The EMG and EDA driver signals exhibit expected aggregated responses of all ATC candidates and control group participants for all types of startle conditions, as shown in Fig. 8. Before aggregating, all startle responses were normalised for each participant by the mean value of the 8 referent AS response magnitudes. This step resulted with a value of 1 for both the EMG- and EDA-based aggregated reference startle response magnitude in Fig. 8. For statistical validation of the shown behaviour, we have conducted multiple one-sample t-tests against reference AS response.

Regarding the EMG-based responses (Fig. 8, left), each group of the average normalised modulated startle responses amplitudes (PPI, FPS, safety) and the group of average normalised SR startle response amplitudes was compared with

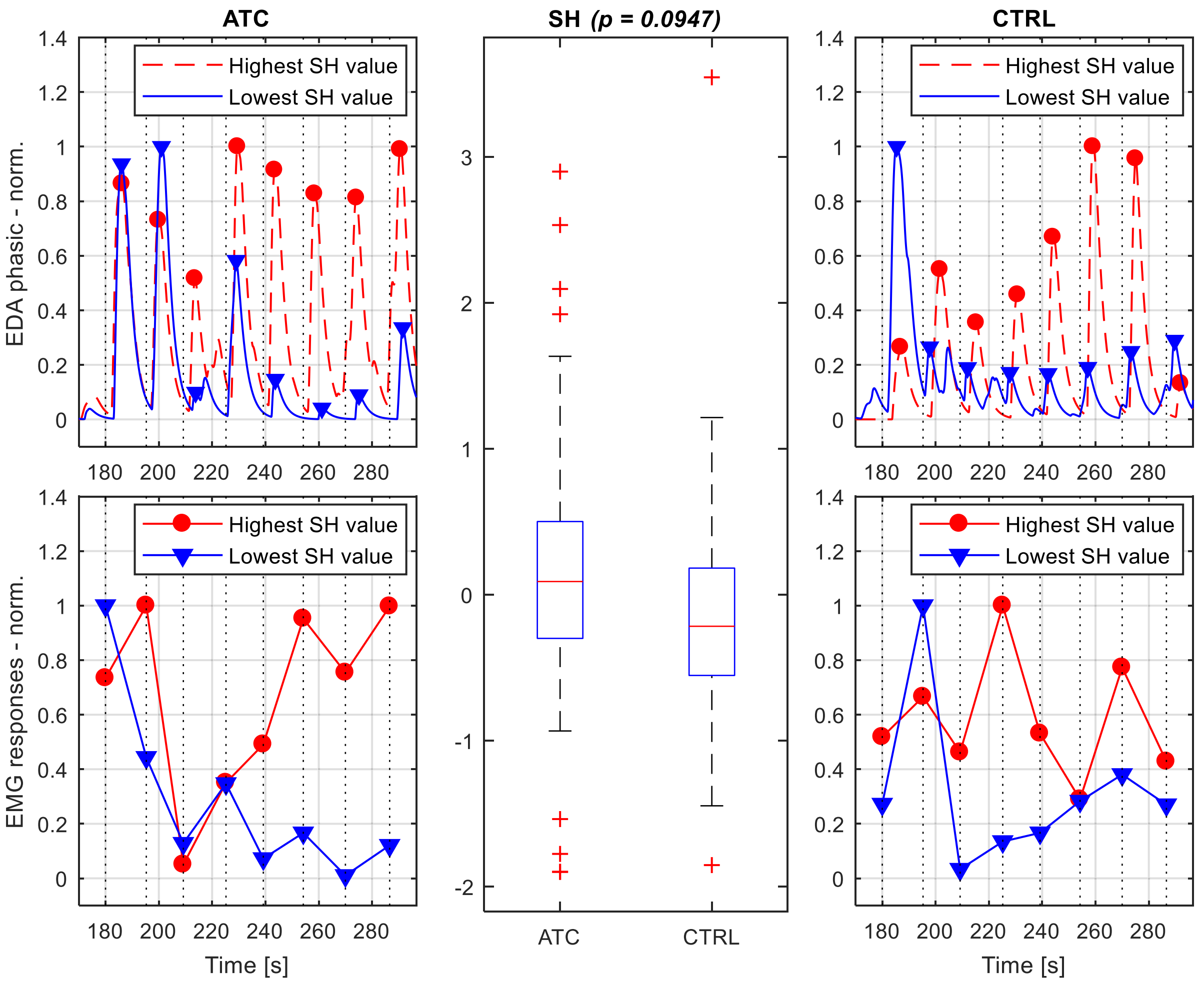

FIGURE 7. Boxplot of SH feature for ATC candidates vs. control group (middle); illustration of ATC candidate with the highest (dashed red) and lowest (solid blue) value of SH (left); illustration of control group participant with the highest (dashed red) and lowest (solid blue) value of SH (right).

the group of average normalised referent startle responses ($M = 1$, $SD = 0$). There was a significant difference between the SR response amplitudes ($M = 1.74$, $SD = 0.92$) and referent startle responses; $t(73) = 6.89$, $p < 0.001$. There was a significant difference between the PPI response amplitudes ($M = 0.12$, $SD = 0.13$) and referent startle responses; $t(73) = -59.69$, $p<0.001$. There was no statistically significant difference between the FPS response amplitudes ($M = 1.09$, $SD = 0.57$) and referent startle responses; $t(73) = 1.33$, $p = 0.1876$. There was a significant difference between the safety AS response amplitudes ($M = 0.86$, $SD = 0.46$) and referent startle responses; $t(73) = -2.71$, $p < 0.01$.

The same statistical analysis was done on the EDA-based responses. There was a significant difference between the SR response amplitudes ($M = 3.20$, $SD = 2.35$) and referent startle responses; $t(73) = 8.08$, $p<0.001$. There was a significant difference between the PPI response amplitudes ($M = 0.69$, $SD = 0.36$) and referent startle responses; $t(73) = -7.34$, $p<0.001$. There was significant difference between the FPS response amplitudes ($M = 1.56$, $SD = 2.27$) and referent startle responses; $t(73) = 2.11$, $p = 0.0385$. There was no statistically significant difference between the safety AS response amplitudes ($M = 0.92$, $SD = 0.88$) and referent startle responses; $t(73) = -0.74$, $p = 0.4616$.

Fig. 9 shows boxplot of PPI, FPS and DSD features obtained from factor analysis, for ATC candidates vs. control group. Wilcoxon-Mann-Whitney two-sample rank-sum test shows: no significant PPI difference between the two groups ($median_{ATC} = 0.0030$, $median_{CTRL} = 0.2823$, ranksum = 1490, $p = 0.4855$, effect size $r = 0.08$); no significant FPS difference between the two groups ($median_{ATC} = -0.1015$, $median_{CTRL} = 0.1399$, ranksum = 1318, $p = 0.2494$, effect size $r = -0.13$); and, no significant DSD difference between the two groups ($median_{ATC} = -0.0379$, $median_{CTRL} = -0.1179$, ranksum = 1454, $p = 0.7579$, effect size $r = 0.04$).

C. MULTIDIMENSIONAL PHYSIOLOGICAL RESILIENCE SPACE

An illustration of aggregated multidimensional physiological resilience space spanned by the 8 selected features is given in Fig. 10, which shows the medians, 25th and 75th percentiles

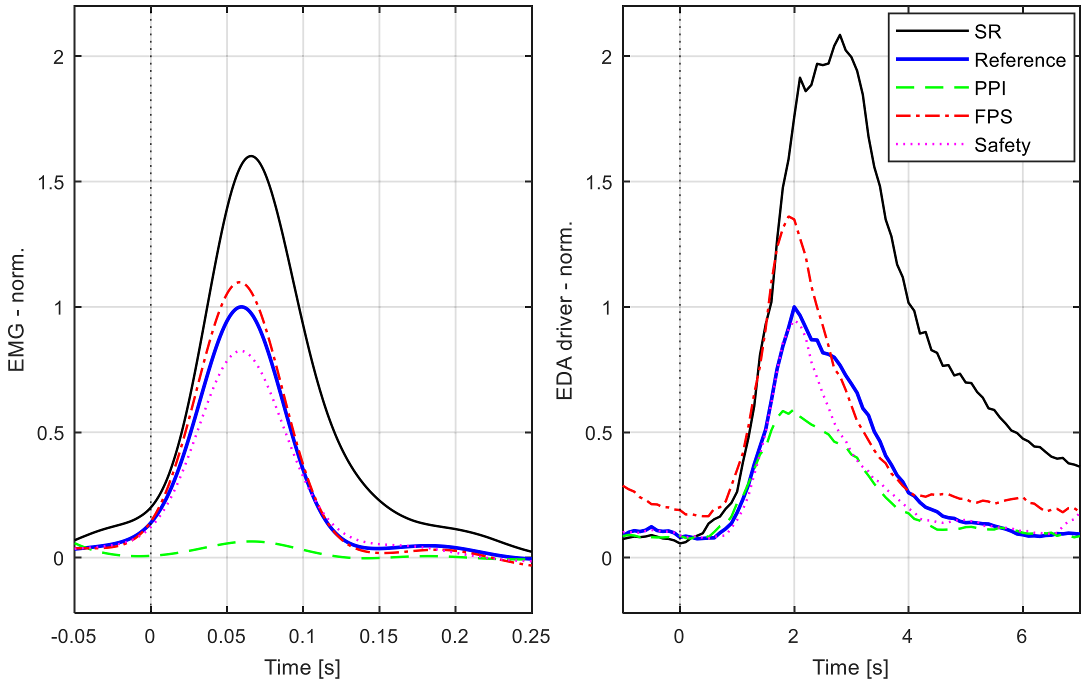

FIGURE 8. Aggregated responses on all AS stimuli for all study participants: EMG (left), EDA driver (right). As expected, the highest aggregated startle responses occur for SR and FPS (Danger) conditions, while startle responses in PPI condition are the lowest on both modalities.

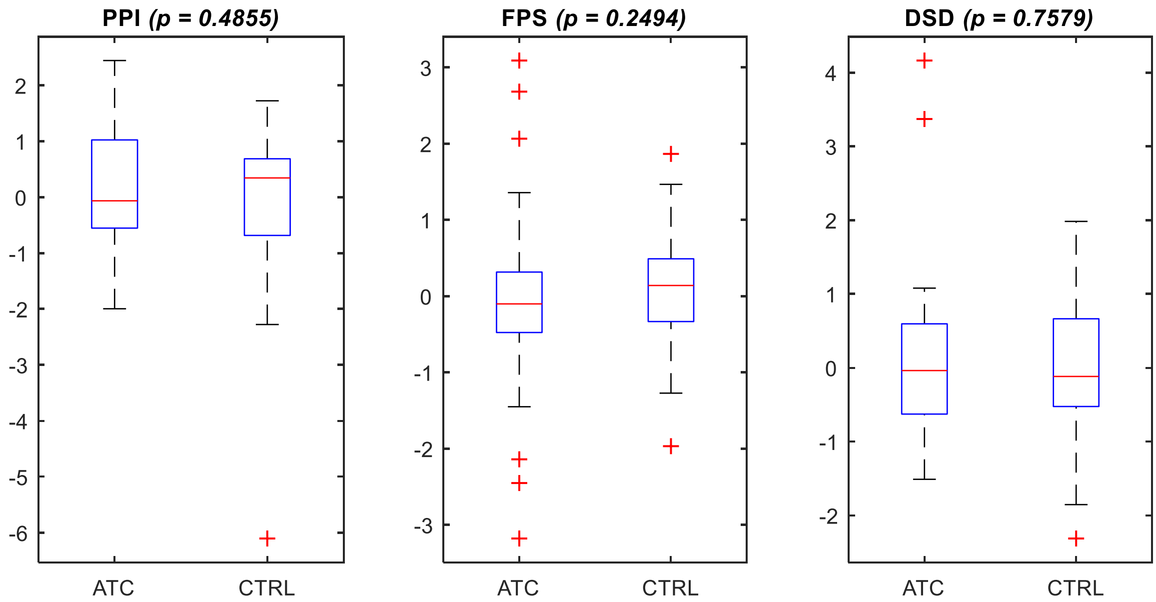

FIGURE 9. Boxplots of PPI (left), FPS (middle) and DSD (right) feature for ATC candidates vs. control group.

for ATC candidates and the control group. Such illustration concisely presents the already obtained results in a way that associates higher values on each axis with higher resilience. Accordingly, in this illustration, the two groups differ the most profoundly on the axes corresponding to RSA, SR and CA features.

V. DISCUSSION

Resilience represents complex multidimensional biological, cognitive, emotional and behavioural phenomena which should be assessed by clusters of different multimodal and multidisciplinary features. In this article, we were focused on 8 relevant physiological features as tools and means for stress resilience assessment. In addition to between-group statistical tests and boxplots of individual features, we provided illustrations of participants with the highest and lowest values of specific features in figures 3-7, for better insight into between-subject variability. Additionally, these illustrations indicate that our computed features reflect the stress-resilience-related physiological phenomena, like RSA, cardiac allostasis, startle reactivity and startle habituation.

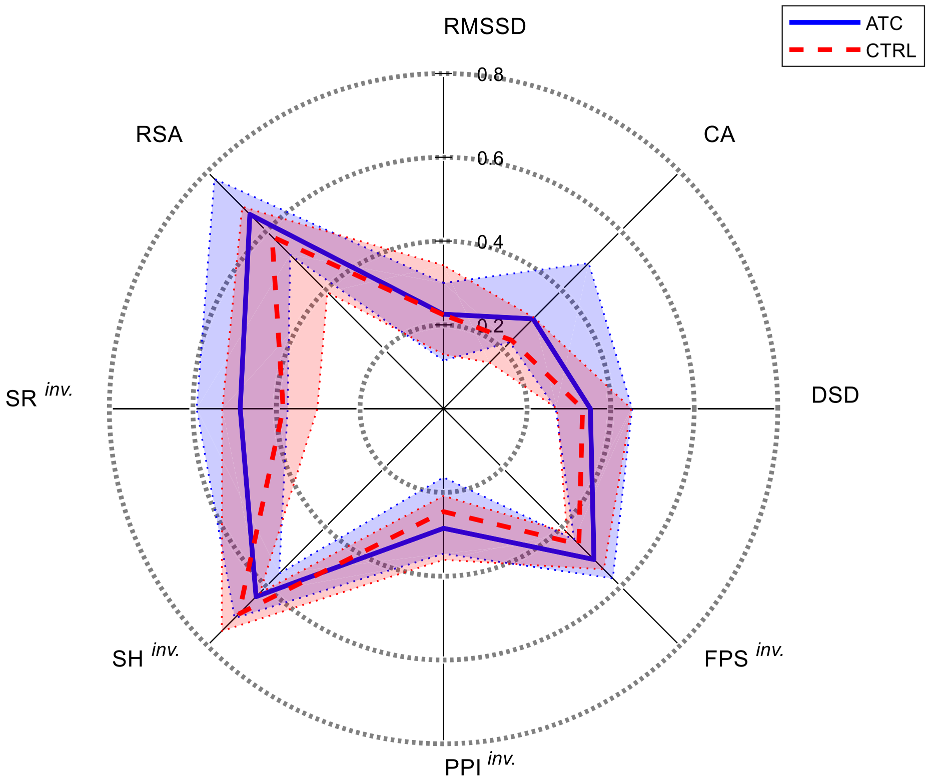

FIGURE 10. An illustration of multidimensional resilience space spanned by 8 selected physiological features. Each axis has been separately normalised from 0 (minimum value across all participants) to 1 (maximum value across all participants).

The results obtained from this research are in line with our expectation that the experimental group of 40 selected ATC candidates is more resilient than the control group, according to the 8-dimensional physiological feature space relevant for stress resilience assessment (Table 1). Specifically, ATC candidates as the more resilient group had significantly higher RSA feature, significantly higher CA feature and significantly lower SR feature than the control group. This was the first time, to the best of our knowledge, that such integrated physiological assessment has been done in a controlled study using the experimental group of ATC candidates in the selection process. Proposed and applied stimulation paradigm is highly efficient, due to a relatively short period (15 minutes) in which we were able to elicit and acquire relevant stress resilience related physiological features.

Our obtained results represent a contribution to the existing literature along the conclusions put forward in a recent review of potential biomarkers of resilience to psychological stress [28]. Specifically, Walker *et al.* [28] concluded that in future experimental protocols, resilience markers should be assessed during baseline as well as during laboratory stressors. Furthermore, they included HRV among the most promising candidate markers to assess during baseline, and startle responses and post-stress cardiovascular recovery among the most promising candidate markers to assess during laboratory stressors. Our research methods adhered to these guidelines, and our obtained results expand the existing empirical evidence base regarding the potential of physiological resilience markers identified in [28].

Moreover, our results presented in the multidimensional physiological resilience space emphasise the importance of combining different resilience markers "to enhance predictive power", as previously advocated by Walker *et al.* [28]. Starting from the top of Fig. 10 in counterclockwise order, RMSSD and RSA features obtained during rest, representing the resting HRV, are relevant for stress resilience and vulnerability [28], [44], [45], [48]; this may be partly related to the importance of resting HRV for long-term maintenance of cardiovascular health, as well as physical and mental wellbeing [47], [84]. Accordingly, resting HRV measures may be regarded as necessary but not sufficient for stress resilience assessment. Continuing in counterclockwise order on Fig. 10, SR, PPI, FPS, DSD and SH features are related to AS reflex, which is an important topic in stress resilience/vulnerability and PTSD research [49], [51], [54], [55], [58], [60]–[63]. Finally, CA feature is related to allostasis, which is one of the prominent concepts in the field of stress resilience [28], [45], [85], [86]. In each of these three categories of features, ATC candidates were in an expected way different from the control group, even though several features exhibited no statistically significant differences between the two groups. Accordingly, these findings emphasise the importance of

FIGURE 11. Laboratory version of IOMS-SRA system based on BIOPAC MP150 vs. field-deployable NINscan system for ambulatory brain and physiologic monitoring in operational environments.

combining resting HRV features, AS-related features and allostasis-related features, in enhancing the assessment and prediction of stress resilience. Most useful features for classification of stress resilience in this paper appear to be RSA, CA and SR features, which showed statistically significant discrimination between ATC candidates and the control group. Therefore, it is reasonable to assume that the subset of these 3 statistically significant features might provide comparable results in terms of "predictive power", with regard to the entire set of the 8 proposed features. However, the research on complex interactions between all these features and their "predictive power" will be undertaken in our future work based on appropriate feature selection and machine learning methods. Along these lines, further empirical validation of the illustrated multidimensional physiological resilience space and its extensions with the most pertinent bio-neuro-psycho-social features of resilience to stress might be important steps toward comprehensive multidisciplinary stress resilience assessment and prediction.

Effect size computation for multiple putative resilience markers within the same research study, such as performed in this paper for the 8 proposed physiological features, should over time accumulate evidence regarding the relative importance of diverse markers for discrimination between individuals with different levels of stress resilience. Assessment of effect sizes has been recognized as a useful aid in the interpretation of research results [87]–[90]; absolute values of effect sizes obtained in this paper for the three statistically significant features, RSA, CA and SR, are all in the range 0.26-0.31, suggesting that these features had comparable between-group discriminative potential. Such effect sizes demonstrate the currently limited ability to distinguish the two non-clinical samples, i.e. ATC candidates as the more resilient group vs. student controls, based on individual features from the set of 8 proposed stress resilience-relevant physiological features. These findings reinforce the notion [7] that any single feature except, perhaps, childhood protective factors, is generally a relatively weak predictor of resilience, and underscore the need [28] to combine different features in future assessments and prediction of stress resilience.

The control group, comprised of 5th-year engineering students, likely represents a stress resilient cohort, relative to the generally healthy population of the same age as our ATC candidates. Relevant literature on this matter, like [91], suggests that college students appear to have somewhat lower 12-month prevalence of various mental disorders than the non-student population of the same age. This might partially explain some of the non-significant results obtained in this paper. Additionally, it would be informative to see how a veteran group of ATCs scores in terms of our physiological features of resilience, in comparison to their sex/age-matched control group. Furthermore, inclusion of non-pre-screened ATC candidates and their comparison with finally selected ATC candidates would be a step forward into the overall screening process regarding physiologically based criteria for inclusion/exclusion from the candidate pool. Therefore, in the follow-up studies, we plan to include cohorts consisting of non-pre-screened ATC candidates, as well as veteran ATCs. Inclusion of these cohorts would allow cross-cohort comparisons that would (a) contextualise current findings relative to effects of occupational exposures, and (b) generate data for developing/refining ATC inclusion/exclusion criteria.

Future work will be focused on the continuation and organisational sustainability of such experimental studies as prospective research. Furthermore, in the focus of future research will be design and development of similar field-deployable version of laboratory IOMS-SRA system applicable for integrated ambulatory brain and multimodal physiological recording, such as NINscan (Fig. 11), that can be used in a variety of field operational environments [64], [92], [93].

Presented concept of technologically assisted stress resilience assessment might also strengthen the quality of the selection process of ATCs, as well as other stressful occupations like first responders, civilian and military pilots, and military personnel.

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