# Inducing and Assessing Acute Mental Stress in Controlled Conditions: Topical Review and Guidelines for Effective Experimental Protocols

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TOPICAL REVIEW

# Inducing and Assessing Acute Mental Stress in Controlled Conditions: Topical Review and Guidelines for Effective Experimental Protocols

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**ABSTRACT** Mental health is influenced by the fast-paced nature of life. In this scenario, stressful events play an important role. Extensive research has been carried out to develop non-invasive devices for stress detection, which primarily use physiological data and, more recently, artificial intelligence algorithms. When developing either a new device or algorithm, tests in controlled environments are preferred, because of the supervision of possible confounding factors while running the experiments. However, because of the extremely subjective perception of stress, the characteristics of the investigated samples, and the conditions under which the experiment is conducted, the data may not be representative of a perceived stressful condition, leading to biases. Given the importance of reliable experimental protocols for stress induction, especially if cortisol level is not monitored, this work aims to present approaches for inducing and assessing acute mental stress in controlled conditions, analyzing the problem from engineering and psychological perspectives. All the phases of the experimental protocol are discussed, examining both the factors that could induce stress and the assessment tools, like questionnaires and physiological signals. The analysis of the latter will be focused on the exogenous factors that may compromise the measures, providing solutions for their mitigation. With this work, researchers with different backgrounds can improve the efficacy of their studies, limiting biases and misleading results.

**INDEX TERMS** Stress monitoring, stress assessment, state anxiety, experimental protocols.

## I. INTRODUCTION

The hectic pace of life and the pressures we are subject to daily affect our mental health, which is a part of the "health" according to World Health Organization [1]. In this scenario, a significant role is played by psychological stress, which manifests when the demands of a situation are perceived to overwhelm the resources we have available to cope [2]. Notably, we perceive stress when facing high-demanding situations, such as financial instabilities and divorces. Unfortunately, this is increasingly true nowadays. A survey by Mental Health UK published in 2024 pointed out that more than 90 % of the participants experienced high or extreme pressure or stress over the previous year [3].

The stress response can be either acute or chronic, depending primarily on the duration of the stressful events [4]. With particular attention to the chronic condition, it has been demonstrated that long exposure to stress may compromise health in older or unhealthy individuals [5]. The onset of cardiovascular diseases [6], metabolic disorders [7] and anxiety [8] are just a few examples of the stress-induced

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diseases, with a direct cost for national health systems and companies, the latter estimated around £28 billion only in the United Kingdom [9].

Given the significant impact of stress and its negative effects, extensive research has been carried out in the last two decades in this regard. A tangible result is the worldwide diffusion of wearable devices [4], [11], [12], which acquire both physical and physiological signals, useful for stress detection, in an easy, reliable and inexpensive way. The heart rate and its variability (HRV) [13], [14], [15] and the electrodermal activity (EDA) [16], [17], [18] are just a few examples of the signals that can be collected by either smartwatches or wristbands, commonly available on the market. The Fitbit Sense 2 smartwatch, along with Whoop 4.0 and the Empatica E4 wristbands, are just a few examples.

In this context, machine learning (ML) [11], [19], [20] and deep learning (DL) algorithms [12], [21], [22], [23] are playing a pivotal role, leading to stress estimation with high accuracy with either unimodal or multimodal approaches [11], [19], [24]. However, despite the great effort from ongoing research, the analysis of cortisol (CORT) levels from biological samples is still today the gold standard for this purpose [25], albeit the procedure is expensive and not immediate [26], limiting its use in real-time applications [27], [28].

Even though the aim is to appraise the users' stress levels in everyday life (i.e., outside the laboratory), testing a new solution, either hardware or software, in controlled conditions is always a good practice; in fact, the possible confounding factors could be limited and the conditions where the experiments take place can be monitored. In this scenario, stressful events need to be artificially recreated. Different approaches could be considered, but cognitive, audiovisual or speech tasks are certainly the most adopted. In this regard, a consistent number of public datasets for ML and DL algorithm development exploit some of the mentioned tasks: e.g., the WESAD [29], CLAS [30], DEAP [31], MuSe [32], MDPSD [33], MMSD [27] and the new StressID [34].

### A. OBJECTIVE AND CONTRIBUTION

The individual stress responses are both extremely non-specific [35] and affected by the relation between the subjects and the environment [2]. Therefore, considering merely the intrinsic stress, i.e., the one induced by the task itself, may be insufficient. This will result in a set of complications, especially if the CORT levels are not monitored: e.g., the investigated signals may or may not manifest evident changes during the task and if they are used to train an ML algorithm, errors in stress estimation could arise. Furthermore, not paying adequate attention to all the exogenous sources of noise affecting the collected signals may lead to misleading results and interpretations.

The above highlights the importance and necessity of a good experimental protocol. For this reason, the presented topical literature review aims to present approaches and solutions for inducing and assessing acute mental stress considering both psychological and technical insights. In the scientific literature, it is possible to find reviews on stress inducement and assessment with different levels of granularity and emphasis. Some explore the type of stressors to be presented during the experiments [36], [37], others focus mainly on the signals and features that can be used for stress analysis [4], [38], whereas others analyze the different algorithms for automatic stress detection [19], [24]. This review is intended to extend the existing literature by providing a practical approach, from participant assessment to physiological data collection, for implementing protocols to induce stress assessment in controlled conditions. To the best of our knowledge, this is the first work aiming to investigate this topic from two distinct perspectives: the psychological and engineering ones. We believe that the contribution of this paper, influenced by the interplay of authors with different backgrounds and expertise, could strengthen future studies by considering stress perception and the sources of inaccuracies that could comprise the data collection and analysis, thus limiting the confounding factors.

### B. STRUCTURE OF THE WORK

The rest of the paper is structured as follows. Section II will provide a detailed presentation of the physiological events that occur in the presence of a stressful condition. Section III will interest stress-inducing approaches in controlled conditions, whereas Section IV will present quantitative tools (questionnaires) for stress assessment and the main sources of inaccuracy that could compromise the mostly adopted signals used for stress detection. Finally, Section V will be dedicated to the conclusion including some final remarks and a future perspective.

## II. PHYSIOLOGICAL RESPONSE TO STRESSORS

Although the human stress response is extremely non-specific, the physiological one is well-defined. When a stressful event (also known as "stressor", i.e. exogenous or endogenous stimuli that evoke a stress response [4]) occurs, a cascade of hormonal and physiological changes manifests, involving both the hypothalamus-pituitary-adrenal axis (HPAA) [40], [41] and the sympathetic-adrenal medullary system (SAMS) [42], [43]. Both the HPAA and SAMS will be presented in this section. Note that in the subsection relative to the HPAA and SAM system we will refer to Fig. 1A and 1B, respectively.

### A. HYPOTHALAMUS-PITUITARY-ADRENAL AXIS (HPAA)

When a stressful event occurs, its severity and emotional impact are assessed by the amygdala which stimulates the hypothalamus in case of threat. This results in the secretion of the corticotropin-releasing hormone (CRH) (1), which travels in the hypothalamic-pituitary portal system to the pituitary gland (2). As a consequence, the anterior pituitary secretes the adrenocorticotropic hormone (ACTH)(2) that flows in the bloodstream until reaching the adrenal glands (3).

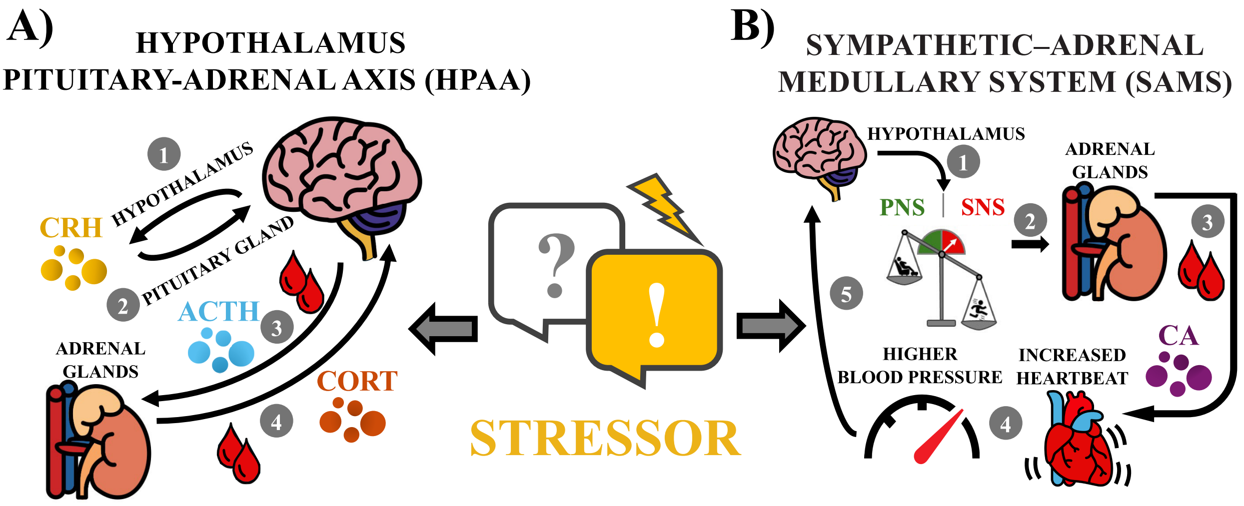

**FIGURE 1.** The physiological response to a stressful event. (A) Activation of the hypothalamus-pituitary-adrenal axis (HPAA), resulting in cortisol secretion by the adrenal glands in the blood flow. (B) Activation of the sympathetic-adrenal-medullary system (SAMS), leading to the onset of the sympathetic nervous system (SNS) activity, i.e., the main component of the *"fight or flight"* response. As a consequence, physiological changes such as increased heartbeat and elevated blood pressure occur. For further details, the reader is referred to [10] where a comprehensive list of all the physiological changes that manifest after the SNS activation is presented.

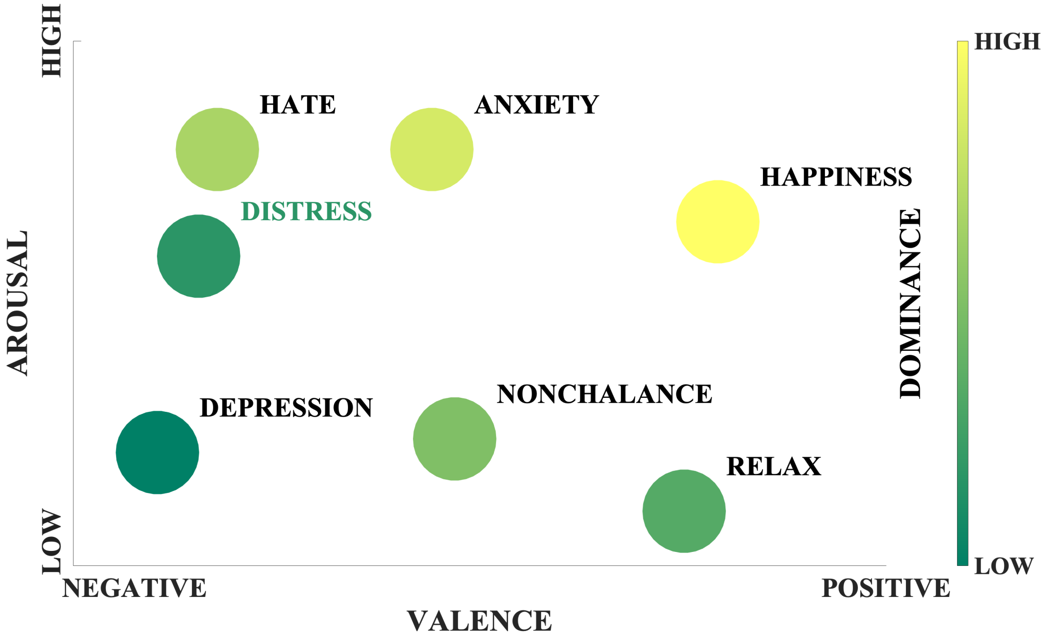

**FIGURE 2.** Graphical representation of a set of emotions on the valence-arousal plane. The dominance dimension is considered through a colour map ranging from dark green (low-dominance) to yellow (high-dominance). Distress (or Stress) is located on the left part of the plane and it is characterized by a low-dominance. The mean values of the tables reported in [39] were considered to locate the emotions in this figure.

Finally, the presence of ACTH induces the release of CORT (4), which is known to be the major stress hormone [44], in the bloodstream. In the acute phase, elevated CORT stimulates catabolic processes to provide the body with extra energy [45], involving the liver, muscles, adipose tissue, and pancreas [46].

### *B. SYMPATHETIC-ADRENAL-MEDULLARY SYSTEM (SAMS)*

Similarly to what happens for the HPAA, the amygdala appraises an ongoing event as a threat and stimulates the hypothalamus (1), which then emphasises the activity of the sympathetic nervous system (SNS - antagonist of the parasympathetic nervous system, PSN) (2). The increased activity of the SNS induces the adrenal glands to secrete catecholamines (CA): adrenaline (epinephrine) and noradrenaline (norepinephrine), into the bloodstream (3). This results in an increase in different physiological parameters, such as the heartbeat and blood pressure (4). Notably, other physiological changes are also involved due to the activation of the sympathetic nervous system. For further details, the reader is referred to [10]. Similarly to what happens with the HPAA, the central nervous system continuously adapts the release of hormones in response to the appraisal of the situation (5).

In contrast to the analysis of HPAA activity, which requires either salivary, hair, urinary, plasma, serum or sweat fingernails samples [26] and can not be performed in real-time [27], the effects of SNS and PNS can be monitored through physiological signals continuously (see Section IV).

## III. INDUCING ACUTE MENTAL STRESS

### A. PSYCHOLOGICAL FUNDAMENTALS

Stress can be divided into two categories: eustress (related to positive events) and distress (associated with negative events) [4], the latter of interest in this paper. Since each emotion is characterized by three components: valence (ranging from positive to negative), arousal (varying from low to high) and dominance (ranging from low to high control on the events) [39], distress can be located on the left side of the valence-arousal plane, i.e., negative valence and high arousal. This condition is also associated with low dominance, as represented in Fig. 2, where other emotions are considered for comparison. Notably, the emotion's location on the arousal-valence plane is obtained considering the mean values reported in [39] tables. Despite the importance of distinguishing between eustress and distress, from now we will simply refer to "distress" with "stress".

From a psychological perspective, when facing a stressful condition, e.g. elicited through a cognitive task, two types of coping strategies may manifest. On one side we have active coping strategies, i.e., approaches including both thoughts and behaviours for managing internal and external demands perceived as stressful [47]. On the other hand, there are the strategies of passive coping, which are conditioned by feelings of helplessness and the need for external support [48].

Because of the subjective stress response, it is difficult to assume that an event will always elicit stress. Notably, individuals will perceive an event as stressful by considering both personal factors, i.e, the subjective perception in the environment [49], [50] and situational factors, i.e., appraisals of the subject with the environment [50], [51]. Therefore, both should be considered to make the event significant, resulting in a stressful response [2]. From now on, we will consider as stressful stimulus a generic cognitive task, better explained in the next section.

The process of generating acute mental stress can be graphically resumed in Fig. 3. The chosen task will induce intrinsic stress in the candidate and hopefully a stressful condition. Notably, stress may subtract cognitive resources and thus a reduction in performance is expected [52]. Based on the above, extrinsic stressors, i.e., due to external factors not related to the task, need to be considered to "boost" the stress perception. For this purpose, the factors (or pressure variables) proposed in [53] could be considered: i.e., audience (and the related factors), competition, reward and punishment, ego relevance and the probability of not being given another chance. In the following, strategies to implement the mentioned factors will be presented.

It has been demonstrated that the sex of the experimenters (or judges) enrolled in the investigation influences the stress perception of the volunteers [54]. In this regard, both men and women show higher levels of CORT when performing in front of judges of the opposite sex [55]. The audience's effect is not limited to the physical presence of people in the room. Indeed, video-recording the subject while performing the task affects the HPAA activation [56] and amplifies both the stress response and the feelings related to threat [57]. Furthermore, this approach would add pressure via at least two factors outlined in [53]: social comparison and social evaluation. If adopted, it is recommended to inform participants that they will be recorded during the experiment and a panel of judges will assess their non-verbal communication, as recommended in [58].

Setting up the experiment like a tournament, where the performances of the participants will be compared, could increase the CORT response, as demonstrated in [59]. The increased stress perception due to competition is linked to social-evaluation threats, that manifest when poor performances are evaluated by judges [60]. In the context of a social evaluation, feedback has a role in the experiments. Derogatory feedback elicits negative affect, i.e. characterized by unpleasant emotions, amplifying negative emotions [61]. In this regard, despite statistical differences in backward counting performances were not obtained, negative feedback induced a higher number of errors if compared to positive feedback in [62].

For what concerns the rewards and punishment factors, people receiving monetary rewards performed worse because of this pressure aspect [63], [64]. On the other hand, punishments could be set up with follow-up interviews that have been shown to create pressure and heighten task engagement in past research [65], even if the interviews never actually materialize. In this regard, it is worth noting that the use of deception in research requires careful consideration and strong justification from an ethical perspective.

Evaluative tasks are additional approaches for boosting stress perception, exploiting ego relevance pressure variables. Assessing the level of intelligence could be a good approach in this regard, especially when students are involved [53].

The mentioned factors could be taken together to boost stress perception in the chosen experiment, in addition to the possibility of not having a second chance to perform the task, similar to what happens in sportive scenarios [66].

In addition, the eight situational properties of stressors listed in [2] could be considered when artificially creating stress, which includes the concepts of novelty, event uncertainty, imminence, duration, temporal uncertainty, ambiguity and timing in relation to the life cycle of the user.

### B. STRESSFUL TASKS

It is possible to induce acute mental stress with different strategies. In this regard, the reader is referred to [67] where a comprehensive table including the clinical and laboratory methods is reported. This section will focus on the common tasks used in the experimental protocols of the public databases mentioned (see Introduction). Moreover, suggestions for their implementation and improved versions will be discussed.

Regardless of the task chosen, a rest phase is usually observed [68]. This step is known as ''Baseline'' and permits subjects to acclimatize and relax before the task(s). There are several approaches for this purpose: let the volunteers relax by providing neutral reading material like magazines [31], [69], ask participants to watch a cross on the screen [31], or relaxing videos [70], with particular attention to the ones involving natural settings, which are considered the most relaxing ones [71]. The temporal duration of the baseline condition is not fixed, but a 15-minute adaptation period is suggested [68].

The Mental Arithmetic Task (MAT) is certainly one of the most adopted cognitive tasks. It is possible to implement it in different ways: e.g, iterative subtraction of a fixed number from a starting one [72], additions [73] or with multiple operations (additions, subtractions, multiplications and divisions) [74]. The temporal length for this task is preferred to be 5 minutes [58]. To increase the stress perception, it is possible to modify the task slightly; for example, by asking the participant to answer the highest number of questions possible [73] or doing the calculation out loud [75]. The MAT is the basis of other cognitive tasks like the Montreal Imaging Stress Task [76]. The latter requires the participants to provide the result of calculus within a certain amount of time, which may increase or decrease depending on whether the user is performing well. To enhance the stress perception, the user's performance is shown in the interface and compared with the previously tested subjects [76]. The Paced Auditory Serial Addition Task (PASAT) is also based on the MAT and can be used as a stressor in controlled conditions [77]. The test is structured as follows: participants are asked to sum adjacent numbers of an array, before the presentation of the new series [78]. The difficulty can be increased by reducing the available time for solving the mathematical operations to as little as 1.2 seconds [78]. Furthermore, by enriching the PASAT with emotional, acoustic and motivational stressors (together with decreased answer time) the Mannheim Multicomponent Stress Test can be obtained [79]. The latter is a solid approach for stress induction in controlled conditions [67], [80] and exploits images with high arousal and negative valence, white noises and monetary punishments as emotional, acoustic and motivational stressors [80], [81]. To increase the complexity of the task, one of the previous factors could be modified (e.g., the cost of each error).

Another widely used cognitive task to induce stress in controlled conditions is the Stroop Colour Word Task (SCWT) [82], which involves identifying the colour of a word shown on the screen. The stimuli in this test can be divided into three groups: neutral (word written in black - used to assess readability), congruent (word written with the same target colour) and incongruent (word written with an ink different from the target colour), with the latter considered the most challenging [36], requiring more time to be completed [83]. Also for this task, reducing the available time to provide the answer will induce pressure on the participants.

The Speech Task (ST) is yet another extensively used method. Participants are asked to prepare a speech in a specific amount of time (ranging from 5 to 10 minutes [84], [85]) and present it in front of a committee without notes. The topics of the speech are variegated. However, the defence against the charge of shoplifting [84] and job interviews [85] are the most adopted [58]. To increase the stress perception during this task, different approaches could be adopted. Preparing a speech under challenging conditions, such as with background noise [86] or within a short time frame (e.g., 3 minutes [56]), are just two examples. Another effective approach is practicing in front of a camera and microphone [87]. Note that the combination of the previous devices is supposed to induce higher grades of social evaluation [88]. Variations of the ST are the Sing-A-Song Stress Test [89] and simple singing stress procedure [90], both demanding the subjects to sing a song rather than to speak.

The above tasks exploit active coping strategies, which are defined in Section III. It is worth noting that it is possible to elicit stress also with other approaches, based on passive coping strategies. Viewing images with high arousal and negative valence (e.g., the ones available in the International Affective Picture System (IAPS) [91] and Open Affective Standardized Image Set (OASIS) [92] datasets), videos (e.g., spider-related videos to individuals who are afraid of the spiders [93]) and performing the cold-pressure test (i.e., immersing one hand in a bucket of cold water for a certain amount of time) are common examples that fall into this category.

Additionally, there are tests that combine some of the previously mentioned tasks. The Trier Social Stress Test [56], [85], which exploits both the ST and the MAT, is certainly the best example, being the most used approach for stress induction in controlled conditions [58]. Different variations of this test exist, differing from the specific samples (e.g., children [94] or adolescents [95]), contexts (e.g., in person [85] or online [96]) and condition (e.g., in a virtual reality scenario [97]). Another example is the Maastricht Acute Stress Test [98], which exploits the MAT and the

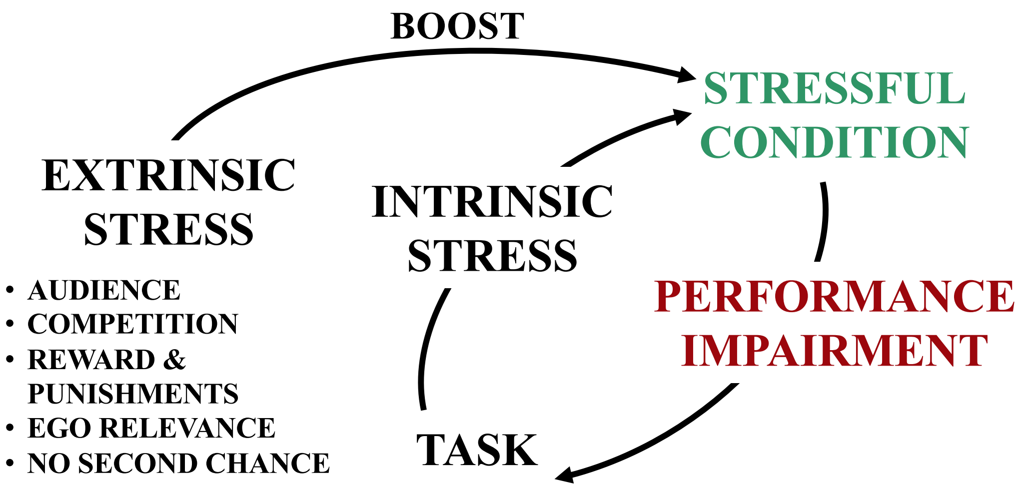

**FIGURE 3.** Generation of a stressful condition through the combination of both intrinsic and extrinsic stressors. The first pertains to task execution, whereas the others involve external factors unrelated to the task. To elicit an extrinsic stress response, the factors presented in [53] could be considered: i.e., audience, competition, reward and punishment, ego relevance and the probability of not having a second chance. The combination of both intrinsic and extrinsic stressors leads to a higher perception of stress by the users (which could subtract cognitive resources [52]) and thus a reduction in performance.

cold-pressure test to enhance the stress perception of the users.

## IV. ASSESSING ACUTE MENTAL STRESS

### A. PARTICIPANT ASSESSMENT

Although being superficial or even missing in some studies, an in-depth analysis of the volunteers taking part in the experiment is fundamental.

When designing an experimental protocol, regardless of the aim of the study, gender-balanced samples are needed. Since differences in responses to stressors exist among sexes [106], grouping data from both males and females may mask the effects due to sex [107]. Moreover, particular attention should be taken when women are enrolled; indeed, their CORT level depends on the luteal phases and may affect emotional and cognitive responses when performing a stressful task [108], [109].

As presented in Section III, it is possible to induce acute mental stress through cognitive tasks. However, it is worth noting that humans react differently based on age and education [110]. Therefore, information relative to both age and education level should be provided, defining specific inclusion criteria when enrolling participants.

Despite existing controversial results about the importance of body weight on neuroendocrine system functioning [111], we believe it is an important feature to consider. Indeed, excessive weight may compromise both optical measurements, e.g., the photoplethysmogram (PPG) [112], and the electrical ones like the electromyogram (EMG) [113]. For further details, the reader is referred to Section IV.

Pharmacological treatments impact behavioural and physiological response (e.g., CORT production) [58]. Therefore, supplements and non-essential drugs should not be consumed in the 24 hours before the experiments. Mixed findings exist on tobacco consumption [58], whereas the assumption of caffeine seems to affect the circadian rhythms [114] and the brain activity [115]. As remarked for the assumption of non-essential drugs, it would be preferable to avoid their consumption the day before the experiments.

The moment of the day when the experiment is performed and the sleeping hours may impact the stress perception. Because of the circadian cycles, which influence the levels of CORT [116], performing a stressful task at different times of the day may lead to different outcomes. For this reason, it is suggested to experiment in the same phase of the day (either in the morning or afternoon) for all the participants. Working night shifts [117] and sleep shifts [118] impact the HPAA activity and, as a consequence, the CORT secretion. This information is missing in most of the studies and particular attention should be taken during participant screening, especially if involving undergraduate students [58], being more prone to manifest chronically limited sleep [119]. Even though the optimal number of sleep hours is strongly subjective and depends on the age [120], we suggest participants sleep 7 to 9 hours before the experiments.

Personality traits (e.g., neuroticism, extroversion), cultural identity and the history of traumatic events are key details to consider when recruiting volunteers for an experiment aiming to explore their stress response. Personality traits can be studied through the multidimensional personality questionnaire, which examines three orthogonal higher-order factors: Positive Emotionality (PEM), Negative Emotionality (NEM), and Constraint (CON) [121]. In this regard, it has

**TABLE 1.** List of questionnaires mostly used in experimental protocols. The table includes the target component to be analysed, the number of questions, values for each mental condition (e.g., low, moderate, or high stress), and the phase of the experiment when the questionnaire can be proposed (e.g., before, between and after the task(s)).

<table>
<tr><th>Questionnaire</th><th>Questions</th><th>Values</th><th>Ranges</th><th>Phase</th><th>Ref.</th></tr>
<tr><td><b>Perceived Stress Scale (PSS)</b></td><td>10<br>(4 - 14)</td><td>0 ↣ 4</td><td><b>Low</b>: [0 - 13] <b>Moderate</b>: [14 - 26] <b>High</b>: [27 - 40]</td><td><b>Before</b></td><td>[99]</td></tr>
<tr><td><b>State and Trait Anxiety Inventory (STAI)</b></td><td>40</td><td>0 ↣ 4</td><td><b>Low</b>: [20 - 37] <b>Moderate</b>: [38 - 44] <b>High</b>: [45 - 80]</td><td><b>Before</b><br><b>After</b></td><td>[100]</td></tr>
<tr><td><b>Visual Analogue Scale (VAS)</b></td><td>1</td><td>0 ↣ 10</td><td><b>Low</b>: [0 - 5[ <b>Moderate</b>: [5 - 8.2] <b>High</b>: ]8.2 - 10]</td><td><b>Before</b><br><b>Between</b><br><b>After</b></td><td>[101]</td></tr>
<tr><td><b>Self-Assessment Manikin (SAM)</b></td><td>3</td><td>1 ↣ 5</td><td><table>
<tr><th>Scale</th><th>Valence</th><th>Arousal</th><th>Dominance</th></tr>
<tr><td>5</td><td>Pleasant</td><td>Excited</td><td>Dependent</td></tr>
<tr><td>4</td><td>Pleased</td><td>Wide-awake</td><td>Powerlessness</td></tr>
<tr><td>3</td><td>Neutral</td><td>Neutral</td><td>Neutral</td></tr>
<tr><td>2</td><td>Unsatisfied</td><td>Dull</td><td>Powerful</td></tr>
<tr><td>1</td><td>Unpleasant</td><td>Calm</td><td>Independent</td></tr>
</table></td><td><b>Before</b><br><b>Between</b><br><b>After</b></td><td>[102]</td></tr>
<tr><td><b>NASA Task Load Index (NASA-TLX)</b></td><td>6</td><td>0 ↣ 100</td><td><b>Low</b>: [0 - 9] <b>Medium</b>: [10 - 29]<br><b>Somewhat high</b>: [30 - 49] <b>High</b>: [50 - 79]<br><b>Very high</b>: [80 - 100]</td><td><b>Between</b><br><b>After</b></td><td>[103]</td></tr>
<tr><td><b>Positive and Negative Affect Schedule (PANAS)</b></td><td>20<br>(10)</td><td>1 ↣ 5</td><td><b>Positive or Negative Affect based on Total Score</b></td><td><b>Before</b><br><b>After</b></td><td>[104]<br>[105]</td></tr>
</table>

been demonstrated that participants with high NEM exhibited great emotional stress [122] when performing the TSST. In terms of cultural identity, individuals from different cultural backgrounds (e.g. Eastern vs. Western cultures) [123], [124], [125] perceive and evaluate stressors differently, as well as volunteers with a history of traumatic events. Individuals with Post-Traumatic Stress Disorder (PTSD) often exhibit heightened stress when faced with unexpected stimuli [126]. All the mentioned factors can profoundly shape how individuals perceive and cope with stressful events, ultimately influencing experimental outcomes, thus justifying the necessity to consider those details during the participant assessment.

All the above should be considered in the preliminary phase of the experiment together with the exclusion of the participants who performed vigorous exercise in the previous 24 hours and those suffering from severe physical and mental health. Overall, to conduct an in-depth analysis of the participant, we refer the reader to [58], where a template considering most of the mentioned factors for this purpose can be found.

### B. SELF-REPORT ASSESSMENT

Once an objective assessment of the participants has been conducted, questionnaires can be adopted to assess subjective experience [127]. Altogether, they differ in target (e.g., stress, anxiety, emotions, mood, mental workload), number of questions, and time required to be filled in. To have a general overview of the participants, at least two questionnaires should be considered during the experimental protocol [58]. In this section, some of the most used will be discussed, providing also details about the number of questions, values for each mental condition (e.g., low, moderate, or high stress), preferred phase to be present them during the experiment (e.g., before, during or after the task). The discussion is summarized in Table 1.

- **Perceived Stress Scale (PSS)**: introduced in 1988 [128], usually exploits 10 questions with the possibility to extend and reduce them to 14 and 4, respectively. It can be used before the beginning of the experiment. The resulting score ranges from 0 to 100 when 10 questions are considered and high levels of stress are usually associated with values between 27 and 40 [100]. Despite being useful and commonly used, it is important to underline that the PSS assesses also a range of stress-related concepts including appraisals, coping, and emotions like anxiety.
- **State and Trait Anxiety Inventory (STAI)**: released in 1983, includes a set of 40 questions, divided into state and trait anxiety scales, to measure the state of anxiety [129]. Whereas the trait anxiety scale is useful to give a feel for the general level of anxiety a participant is likely bringing into the experiment (e.g., like a confounding factor), the state anxiety scale is useful to indicate if anxiety changes as a result of (i.e., before and after) an experimental manipulation such as a

high-pressure or stressful task. It can be presented to the volunteers before and after the task and the resulting score ranges from 0 to 80. High levels of anxiety are related to scores between 45 and 80 [100].

- **Visual Analogue Scale (VAS)**: used to assess the symptom severity related to a disease, it is a common tool in the clinical practice [130]. In the context of stress measurement, a coloured scale (codified in 10-points) is preferred [131]. It is extremely rapid and misunderstandings can be avoided [132]. Because of its rapidity, it can be presented to the participants not only before and after the experiment but also between tasks. The resulting score ranges from 0 to 10 and a score between 8.2 and 10 can be linked to a high-stress perception, according to [101]. Similarly to the visual analogue scale, other questionnaires can benefit from its rapidity. In this regard, the reader is referred to the stress [133] and anxiety [134] thermometers and the immediate anxiety measurement scale [135], just to mention a few.
- **Positive and Negative Affect Schedule (PANAS)**: introduced in 1988 [104], it consists of 20 questions, 10 measuring the positive affect (e.g., interested, active) and the remaining the negative one (e.g., irritable, nervous) [136]. With this questionnaire, it is possible to quantify mood and emotions. The prevalent affect (positive or negative) is the one having the highest score. Despite the existence of a shorter version with only 10 questions [105], it is not as rapid as the visual analogue scale. For this reason, it is preferable to present it before and after the experiment.
- **Self-Assessment Manikin (SAM)**: it is a non-verbal tool to assess emotions and was introduced in 1994 [137]. It explores three principal dimensions: valence, arousal and dominance. This questionnaire is rapid to be filled out and can be presented to the participants not only before and after the experiment but also between tasks. Notably, stress conditions are associated with negative valence, high arousal and low dominance (see Fig. 2).
- **NASA-Task Load Index (NASA-TLX)**: it is a questionnaire used to assess both the physical and mental workload of a task, exploring six dimensions: mental, physical, and temporal demand, along with performance, effort, and frustration [138]. The resulting score ranges from 0 to 100. A score between 50 and 79 is associated with a high mental workload, whereas if the total score falls between 80 and 100, it can be classified as very high demand [103]. It is possible to consider variants of the presented questionnaire: e.g., the SURG-Task Load Index and the SIM-Task Load Index. The first explores mental, physical and temporal demands together with task complexity, situational stress and distractions [139], whereas the latter includes additional factors like perceptual strain, task control and presence [140], making it suitable for demands of simulated environments in virtual reality.

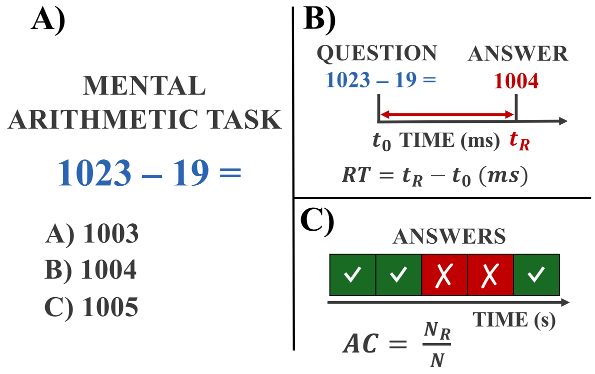

**FIGURE 4.** **A) Example of question for the mental arithmetic task. (B) Reaction time (RT) refers to the time between the question's display ($t_0$) and the moment when the user provides the answer ($t_R$). (C) Accuracy considers the number of corrected answers ($N_R$) over the total number ($N$).**

Collecting data through questionnaires is certainly an immediate and inexpensive strategy. However, attention should be taken. Because of a strong subjective component and social desirability bias (i.e., the tendency to over-report more desirable qualities and under-report socially undesirable actions [141]), they can not be completely reliable. This results in a set of limitations, including biases in the estimations [34]. In addition, questionnaires along with the level of CORT and many other biological markers cannot be collected continuously [28].

### C. PERFORMANCES

With particular attention to the MAT and the SCWT, the number of correct answers and reaction times (RT) need to be monitored for the whole duration of the tasks [142]. RT can be defined as the time between the onset of the question and the moment in which the user provides the answer, whereas the number of correct answers over the total number of questions in a specific temporal interval is known as accuracy (AC) (see Fig. 4). Performing a task in acute stress conditions will impact both RTs and ACs. More specifically, an increase of RT [143], [144] and a decrease in AC [145], [146] is expected.

By combining the mean RT of the correct answers and AC the inverse efficiency score (IES) can be obtained:

$$IES = \frac{RT}{AC} \tag{1}$$

It is usually measured in milliseconds and takes into account both the velocity and precision while performing a specific task. Notably, it is possible to measure this index also for a limited number of questions to compare the performances over the tasks. In this case, the Equation (1) can be adapted as follows:

$$IES = \frac{\frac{\sum_{k=1}^{K} RT_k \cdot a_k}{(\sum_{k=1}^{K} a_k)}}{\frac{(\sum_{k=1}^{K} a_k)}{K}} = K\frac{\sum_{k=1}^{K} RT_k \cdot a_k}{(\sum_{k=1}^{K} a_k)^2}$$

$$a_k = \begin{cases} 1, & N_k = 1, \\ 0, & \text{elsewhere} \end{cases} \tag{2}$$

where $K$ is the number of questions in the interval, $N_k$ is the answer to the $k^{th}$ question, $RT_k$ is the reaction time at the $k$ position and $a_k$ is a binary coefficient that can be either 1 if the user answers correctly to the question $N_k$ or 0. Note that the numerator takes into account the mean reaction time of the correct answers, whereas the denominator is the accuracy. However, attention must be paid to the estimation of this parameter. Indeed, the high number of errors will bias the IES estimation, also making it unstable because only a few RT values are considered. For this reason, as suggested in [147], IES should be estimated when there is a strong correlation between RT and AC, considering the cases when the number of errors is low.

If the ST is considered, features relative to the performance could be estimated as well. In this regard, metrics like the number of words per minute and word productivity (i.e., the ratio between the number of effective words and the total number), could be assessed. However, pauses (i.e., duration of time between words) and their number seem to be the ones mostly affected by stress conditions [84].

### D. PHYSIOLOGICAL SIGNALS

As a direct consequence of the HPAA and SNS activation, changes in subjects' homeostasis manifest, most of which can be detected through physiological signals.

Given the number of reviews focusing mainly on the signals and relative features that could be used for stress detection [4], [24], which the reader can rely on for further details, this section will have a practical connotation. A comprehensive list of the investigated signals is presented in Table 2, reporting the bandwidth of each signal (with the suggested sampling frequency), the main exogenous sources of noises and the suggested approaches to mitigate (when possible) their effect. Note that the software approaches to mitigate the effects of external sources of noise will not be considered.

Before analyzing the signals for stress detection, it is worth noting that data are sampled at a constant rate, and their Fourier transform results in periodic repetitions (aliases) of the original signal's frequency components. To avoid aliasing, a low-pass filter with a cutoff below the Nyquist limit (half the sampling rate) should be used before sampling to remove higher frequencies. This ensures accurate signal representation without high-frequency distortion [148]. With particular reference to the sampling frequency, Table 2 reports the common sampling frequencies for the investigated signals that exceed 3 times the maximum bandwidth of the signal, to compensate for the non-idealities of the anti-aliasing filters, which are part of the acquisition chain.

Heart rate variability (HRV) is widely adopted for stress detection [13], [14], [15]. However, attention should be taken when estimating it. Formally speaking, we are dealing with HRV only if the processed signal is the electrocardiogram (ECG), whose frequency band is mostly between 0.05 and 100.0 Hz [178]. On the other hand, if the photoplethysmogram (PPG) is considered, we are addressing the pulse rate variability (PRV). Note that the frequency band of PPG is usually between 0.01 and 10.0 Hz [179] and the suggested sample frequencies for the estimation of HRV and PRV are 250.0 Hz [180] and 50.0 Hz [153], respectively. Although a solid consensus regarding the applicability of the PRV as a direct substitute for the HRV is missing [181], [182], some studies demonstrated a correlation between the HRV features with the ones estimated through PPG, but only in rest conditions [181], [183], [184]. Nonetheless, it is worth pointing out that a high correlation does not imply interchangeability. Two main factors that do not make HRV and PRV interchangeable are the blood pressure [182] and the pulse-transit-time (i.e., the time required for the arterial pulse wave to travel to the sensor, PTT) [185], [186], which depends on the blood pressure as well [187]. Notably, since there is also an unknown time related to aortic valve opening, measuring the vascular transit time rather than the PTT is preferred [187].

For what concerns data acquisition, both ECG and PPG are susceptible to motion artifacts [188], [189], [190] that, if not attenuated, could compromise the signal-to-noise ratio (SNR). Different environmental factors affect the quality of the measurements: the ECG is influenced by the skin-electrode interface and by electromagnetic interference (EMI) [150], [191], whereas PPG is affected by the environmental light and temperature [112], [150]. Additionally, the skin tone [152] and fat thickness influence the quality of the PPG [112], [152]. To reduce the effect of the previous sources of inaccuracy, skin preparation [151], short cables [150], wet electrodes [151] and high common-mode-rejection-ratio (CMRR) amplifiers should be adopted for the ECG. On the other hand, if PPG is considered, it is possible to partially mitigate the previously highlighted sources. Keeping both the room temperature and humidity constant is certainly a good approach, along with the optical shielding [112]. Furthermore, to enhance the quality of the PPG, locations with high skin perfusion should be considered [192], e.g., the finger and the ear [193]. The effect of the skin tone could be slightly attenuated by increasing the wavelength of the light source [112]. However, it is not always possible to change this parameter. Devices collecting PPG (e.g. wristbands) are perfectly suited for long-time measurements, whereas ECG devices exploiting wet electrodes are sub-optimal since skin-irritation may occur [194]. Capacitive electrodes could be adopted as alternative [195], e.g., embedded into a

**TABLE 2.** Table including the widely adopted signals for stress detection. Each line of the table includes the type of signal, its frequency band (with commonly adopted sampling frequency), the main sources of inaccuracy (e.g., interference and noise) and the recommended actions to mitigate their effects.

| Signal | Frequency Band (Sampling Frequency) | Exogenous Sources of Noise | Suggested Acquisition conditions | Ref. |
|---|---|---|---|---|
| **Electrocardiogram** | 0.05 ↣ 100.0 Hz<br>(500.0 Hz) | • Motion artifacts,<br>• Electromagnetic interference,<br>• Skin-electrode interface. | • Skin preparation,<br>• Short and not stretched cables, with wet electrodes,<br>• High CMRR amplifiers. | [149]<br>[150]<br>[151] |
| **Photoplethysmogram** | 0.01 ↣ 10.0 Hz<br>(50.0 Hz) | • Motion artifacts,<br>• Ambient factors (temperature, humidity, light),<br>• Skin tone,<br>• Sensor location. | • Controlled temperature, humidity and light,<br>• Optical shielding,<br>• Site with high vascularization (e.g, finger and ear),<br>• Wavelength selection (if possible). | [112]<br>[152]<br>[153] |
| **Electrodermal Activity** | 0.03 ↣ 0.5 Hz<br>(4.0 Hz) | • Motion artifacts,<br>• Ambient factors (temperature and humidity),<br>• Skin-electrode interface. | • Controlled temperature and humidity,<br>• Pre-gelled electrodes,<br>• EDA conductive gel (ECG and EEG ones are not suitable),<br>• Appropriate sites for measure: e.g., finger, foot and shoulder. | [154]<br>[155]<br>[156]<br>[157] |
| **Electromyogram** | 1.0 ↣ 500.0 Hz<br>(2000.0 Hz) | • Motion artifacts,<br>• Electromagnetic interference,<br>• Skin-electrode interface. | • Skin preparation,<br>• Short and not stretched cables, with wet electrodes<br>• High CMRR amplifiers,<br>• Differential measurements.<br>• Electrodes with fixed inter-electrode distance. | [158]<br>[159] |
| **Electroencephalogram** | 0.1 ↣ 40.0 Hz<br>(500.0 Hz) | • Motion artifacts,<br>• Electromagnetic interference,<br>• Skin-electrode interface, | • Short and unstretched cables, with wet electrodes<br>• High CMRR amplifiers,<br>• Differential measurements. | [150]<br>[160] |
| **Surface Temperature** | 0.001 ↣ 0.1 Hz<br>(1.0 Hz) | • Skin tone,<br>• Skin to sensor distance,<br>• Ambient factors (e.g,, wind, temperature, wind's speed). | • Fixed distance between the skin and the sensor,<br>• Controlled ambient temperature. | [161]<br>[162] |
| **Respiration** | 0.1 ↣ 1.0 Hz<br>(4.0 Hz) | • Modulation of the cardiac activity: see *Electrocardiogram* and *Photoplethysmogram*.<br>• Chest-wall movements:<br>-- Motion artifacts,<br>-- Temperature and humidity (for piezoelectric sensors). | • Modulation of the cardiac activity: see *Electrocardiogram* and *Photoplethysmogram*.<br>• Chest-wall movements:<br>-- Sensor in a chest strap,<br>-- Protection of the piezoelectric sensor with shielding materials. | [163]<br>[164]<br>[165]<br>[166]<br>[167] |

**TABLE 2.** ***(Continued.)*** **Table including the widely adopted signals for stress detection. Each line of the table includes the type of signal, its frequency band (with commonly adopted sampling frequency), the main sources of inaccuracy (e.g., interference and noise) and the recommended actions to mitigate their effects.**

| Signal | Frequency Band (Sampling Frequency) | Exogenous Sources of Noise | Suggested Acquisition conditions | Ref. |
|---|---|---|---|---|
| **Pupillogram** | $0.2 \rightarrowtail 4.0$ Hz<br>(20.0 Hz) | • Motion artifacts,<br>• Ambient factors (light, temperature). | • Fixed eye-camera distance,<br>• Controlled ambient temperature (20-23°C),<br>• Controlled ambient light. | [168]<br>[169]<br>[170] |
| **Speech** | $0.1 \rightarrowtail 20.0$ kHz<br>(44.1 kHz) | • Environmental noise,<br>• Recording distance,<br>• Type of microphone. | • Condenser microphone with pop-filters,<br>• Fixed distance from microphone (unidirectional),<br>• Mono recording with uncompressed format (WAV),<br>• Soundproof room (if possible). | [171]<br>[172]<br>[173]<br>[172] |
| **Inertial Measurement Units** | $0 \rightarrowtail 15.0$ Hz<br>(50.0 Hz) | • Ambient factors (temperature, humidity, light),<br>• Vibrations,<br>• Electromagnetic interference. | • Controlled ambient, temperature and humidity,<br>• Manual calibration,<br>• Shielded wires. | [174]<br>[175]<br>[176]<br>[177] |

garment [195], [196]. However, this solution is more prone to motion artifacts [197].

The electrodermal activity (EDA) is a well-established for stress detection [16], [17], [18] and has two components [198]: the skin conductance level (SCL), and the skin conductance response (SCR), also known as tonic and phasic components, respectively. Of the two, the SCR is one of the major since it is an indirect index of SNS activation [199]. The frequency components of this signal fall between 0.03 Hz to 0.5 Hz, [156], [157], with most of the power between 0.045 and 0.15 Hz [156]. For what concerns the sampling frequency, a minimum of 2.0 Hz is suggested [200]. Data acquisition is mostly influenced by motion artifacts [201] and environmental conditions like humidity and temperature [18], [155], [202], the latter mostly affecting the tonic component rather than the phasic one [202]. It is preferable to monitor both temperature and humidity and to use pre-gelled electrodes, with EDA conductive gel, for data acquisition [155]. To enhance the quality of the measure three areas are suggested in [203]: fingers, foot and shoulders. Overall, the measurement is not intrusive, it requires a little time to be set up and, if included in wearable devices, is meant for long-term measurements [204].

The surface electromyogram (EMG) and the surface electroencephalogram (EEG) are electrical measurements, relative to muscle contraction and neural activity, respectively. Both the EEG [23], [205], [206] and the EMG [22], [207], [208] are used as signals for stress detection. The frequency band of the EMG is between 1.0 and 500.0 Hz and the most used sample frequency is around 2.0 kHz [158]. On the other hand, the EEG has a frequency band between 0.1 and 40.0 Hz and a good sample frequency value could be around 500 Hz. Electromagnetic interferences can influence both the EMG and EEG [209], [210], which can be reduced using amplifiers with appropriate CMRR and differential measurements. In this regard, particular attention is necessary when considering differential measurement. Indeed, impedance mismatches due to the skin-electrode interface may vanish the rejection of the common mode. Short and not stretched cables in combination with wet electrodes should be used to enhance the SNR [158], [159] and reduce the effect of motion artifacts. Note that both are susceptible to that artifact. This is true, especially for the EEG [211], because of the strong overlap between the frequencies of the motion artifacts and the brain rhythms. Regarding the time for the set-up, the EEG is certainly the most time-consuming. On the other hand, the time required for the EMG set-up increases with the number of electrodes [158].

Surface body temperature (SBT) is another physiological signal that could be considered for our purpose [212], [213], [214]. Indeed, to ensure homeothermy, the SNS induces peripheral vasoconstriction in case of acute stress [215] and consequently a reduction of the surface temperature [216].

SBT oscillates with frequencies ranging from 0.001 to 0.1 Hz [162] and a sampling frequency of 1.0 Hz is certainly more than enough for data collection. If measured through non-contact infrared thermometers, surface body temperature is affected by both environmental factors (e.g., ambient temperature, humidity, wind, heat sources) and acquisition conditions (e.g., distance and angle [161], [217]). Similarly to the PPG, SBT is influenced by the skin tone [161]. To overcome some of the previous aspects, it is recommended to monitor the environmental factors and guarantee a fixed distance between the sensor and the skin during the experiment.

The increased activity of the SNS impacts the respiration of the subjects. Since the respiration signal has a frequency band between 0.1 and 1.0 Hz [163], [167], a sampling frequency of 4.0 Hz is recommended. Despite the numerous contact-based methods for estimating the respiration signal [166], this section will focus on methods based on chest-wall movements and the modulation of cardiac activity. The first exploits sensors placed on the chest wall (e.g., resistive, capacitive, inductive and fibre optic sensors [166]), whereas the latter the ECG [164] and PPG [165]. If the respiration signal is estimated through the heart-related signals, the problems relative to ECG and PPG will be inherited. On the other hand, if the chest-wall movements are considered, the main source of inaccuracy is related to sensor movements (i.e., motion artifact), not related to the chest. For this reason, it is necessary to ensure good contact between the sensor and the skin, which could be embedded into a chest strap. The environmental conditions do not influence significantly the sensors used to analyze the chest-wall movements, except for the strain gauges based on piezoelectric sensors, which are sensitive to temperature and humidity changes [166], leading to output drifts. For this reason, it is recommended to cover the sensor with protective materials [166]. Overall, both the presented approaches show low set-up times and the possibility for long-term acquisitions.

The SNS influences also pupil size [218], [219] and studies demonstrated the efficacy of considering the pupil diameter for stress analysis and assessment [220], [221]. Its frequency range oscillates between 0.01 and 5.0 Hz [222] and the suggested sampling frequency is 20.0 Hz [168], [169]. Concerning the exogenous sources of noises that could compromise the measurement, motion artifacts and ambient conditions (i.e., light and temperature) are certainly the most influential [169], [223]. Thereby, experiments should not be performed in very dark or very bright environments [168], maintaining the distance between the eyes and the camera fixed (to reduce the head's movement) and monitoring both the background and room illuminance during the experiments [169], [170]. Because of SNC activation in cold environments, the suggested temperature for the experiment is between 20 and 23 °C [169].

As introduced in Section IV, changes in the speech manifest because of stressful situations. For this reason, speech analysis can be exploited for stress assessment [224], [225]. The frequency range of this signal is mostly between 0.1 and 8.0 kHz. Although higher frequencies may manifest during data acquisition, they are usually exploited for user localization [172]. The main sources of exogenous noise during the data collection are related to the environmental noise, the distance from the microphone and the type of device used [173]. To mitigate their effect, it is recommended to use condenser microphones with pop-filter, a set-up for keeping fixed the distance from the microphone and use a mono recording with uncompressed format (e.g., Waveform Audio File, WAV) [173].

Finally, data from the inertial measurement units (IMU) can considered as well. In most cases, accelerometer data is coupled with other signals [226], [227], [228], whereas sometimes they are the only signal considered [88], [229]. The maximum bandwidth of the human body movements falls between 10.0 and 15.0 Hz according to [175]. For this paper, the focus will be on IMU based on micro-electronic-mechanical systems (MEMS). The main external factors compromising their output are temperature changes, humidity, vibrations, shocks and electromagnetic fields [174], [176]. For this reason, the environmental condition should be monitored. If low-cost IMUs are used, usually coming with smartwatches or smartphones, additional systematic errors arise. In this regard, to mitigate both errors and possible drift recalibrations can be considered, also without external devices [177]. On the other hand, to mitigate EMI's effect shielded wires and cases should be used. Overall, they require little time to be set and can be leveraged for long-term acquisitions if embedded in either wristbands or smartwatches.

### E. DATA ANALYSIS

The experimental protocol pipeline can be graphically summarized in Fig. 5, which is divided into four phases: the first implies the analysis of the participants and the self-assessment reports (the second one to be presented to the participants after the experiment's conclusion); the second phase pertains to the baseline condition in which the participants acclimatize and the physiological signals begin to be collected; the third involves again a self-assessment report to be filled out before the onset of the stressful event; and the final one, relative to the stress-inducing task. The types of questionnaires used may vary across different phases of the assessment. For instance, the initial self-report assessment might include questionnaires like the PSS, STAI, VAS, and PANAS, whereas the second assessment could utilize a similar set, excluding the PSS. In contrast, the final assessment may incorporate questionnaires like the STAI, PANAS, SAM, VAS, and NASA-TLX.

For ease of understanding, Fig. 5B and 5D show four physiological signals, commonly adopted for stress assessment, with one feature each. Data come from the WESAD database [29] and are relative to subject S14. The ECG was collected using a standard three-point measurement, the EMG

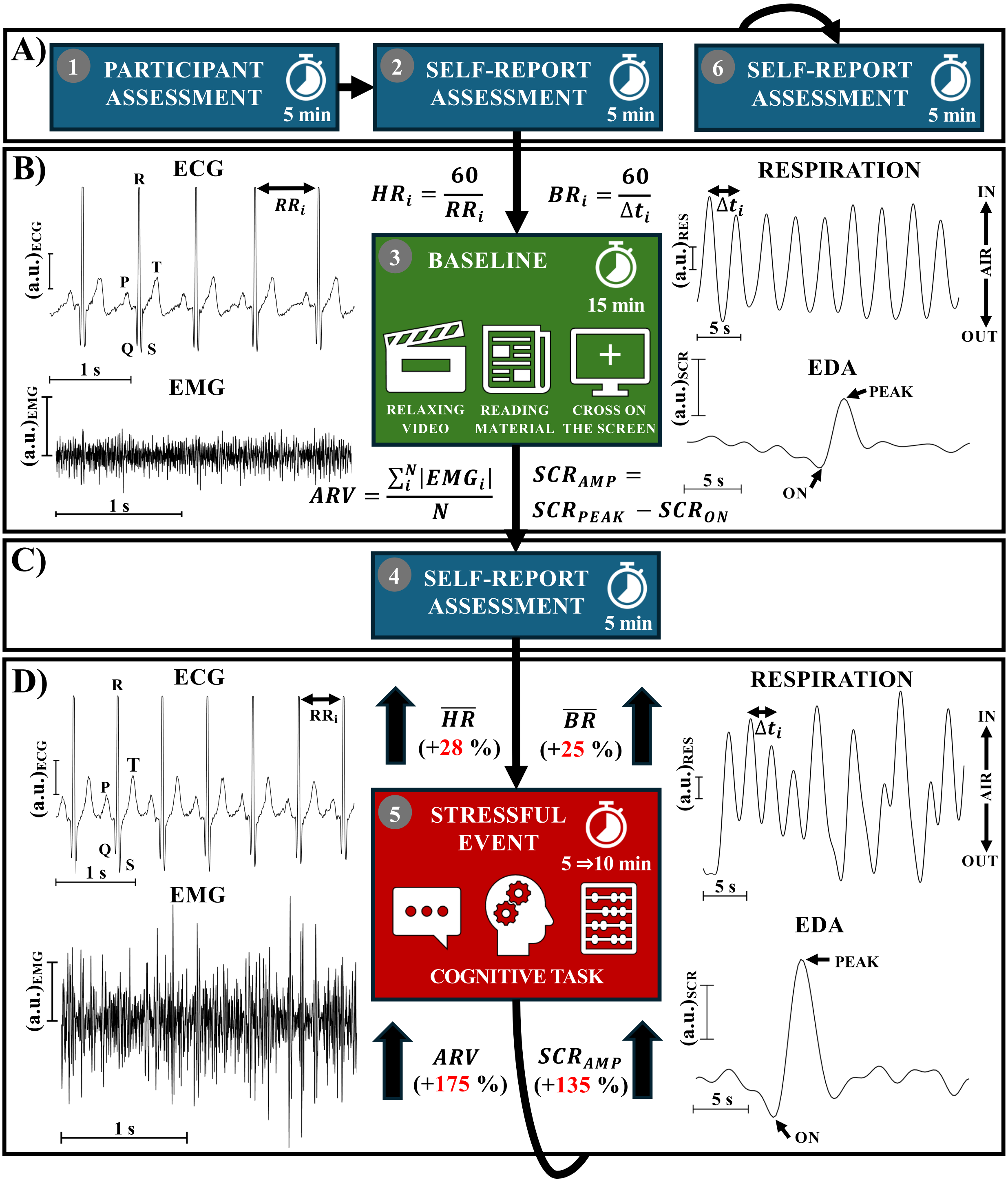

FIGURE 5. Graphical representation of the experimental protocol pipeline in four phases: A) Participant and self-report assessment, the latter repeated twice: at the beginning and end of the experiment B) The baseline condition, which is meant to let the participants acclimatize. Reading magazines, relaxing videos or looking at a cross on the screen are common approaches adopted in this phase, while physiological signals are recorded. In this example, signals like the ECG, EMG, respiration and EDA are reported. The experimental data come from the WESAD database [29], subject S14. The reported signals are treated as follows: the ECG is filtered between 100 mHz and 100 Hz, the EMG is high-pass filtered at 10 Hz (to mitigate the motion artifacts), the respiratory signal is filtered between 100 mHz and 1 Hz, whereas for the EDA signal, the onset and peak of SCR are obtained with the Neurokit2 toolkit (function *eda_process* with method *"neurokit"*). Features like the heart rate (HR), breath rate (BR), average rectified value (ARV) of the EMG, and SCR amplitude are reported as examples. C) Self-assessment report, before the onset of the stressful situation, which aims to elevate psychological pressure before they start the task. D) Stressful event induced through a cognitive task. Changes in the physiological signals occur e.g., elevated values of HR and BR (average) and increased ARV and SCR amplitude. The blocks are numbered from 1 to 6, and an approximate each step's duration is reported.

of the trapezius, which is commonly used in experiments for stress induction and assessment, was collected in a bipolar mode, the respiration signal was captured using an inductive plethysmographic sensor, and the EDA was measured on the subjects' wrists. All signals were recorded with the RespiBAN at a sampling frequency of 700 Hz, except for the EDA signal, which was collected at a sampling frequency of 4 Hz using the Empatica E4. The baseline condition allows for a comparison of the features and signals with the stress condition, which in this case was induced using the TSST. The signals were processed with MATLAB® (version 2024a) and Python$^{TM}$ (version 3.11.3). The analysis of the EDA was conducted with the Neurokit2 toolkit (version 0.2.7).

In this example, the physiological signals and their respective features exhibit changes in response to stress conditions, e.g., higher average values of heart rate (HR) and breathing rate (BR), higher amplitude of the EMG signal (estimated through the average rectified value, ARV), and higher amplitude of the tonic component of the EDA signal, compared to the baseline condition. Note that this aligns with the findings of [4].

However, these are not the only features used to assess the stress response of the candidates; many others may be taken into consideration. In this regard, we refer the reader to a review of the signals and features that are related to stress response [4] for further insights.

The variety of signals and features for stress detection necessitates the use of multi-modal data fusion approaches and time-series analysis. To date, several reviews studied this topic outlining the advantages and disadvantages of various algorithms and methods for stress analysis [11], [20], [24], justifying the benefit of multi-modal approaches to estimate stress with high accuracy [11], [24]. For this reason, for the sake of completeness, we will just mention in this section some of the most common approaches that can be adopted for stress analysis, by redirecting the reader to the papers mentioned earlier for additional details. As mainly adopted algorithms we can mention: Support Vector Machines, Random Forests, Fuzzy Logic Algorithms, K-Nearest Neighbours, Logistic Regression, Naive Bayes classifiers, Ensemble Methods, Artificial Neural Networks, Convolutional Neural Networks and Recurrent Neural Networks [11], [12], [19], [20], [21], [22], [23].

The mentioned methods vary in complexity, training time, and reliance on features. However, the type and the conditions in which the data are collected before the training of any model remain crucial factors, influencing its performance. What has been said could partially justify the consistent heterogeneity in terms of performance in the literature [11], [19], [24]. All the above underlines once again the importance and need for a well-structured experimental protocol, from the assessment of the participants to data collection and data analysis. Doing so would provide more relevant data to the algorithms and, consequently, better performance in terms of stress detection.

## V. CONCLUSION

One of the main limitations of a scientific study, especially when humans are involved, is the lack of reproducibility, often caused by inconsistent methodological reporting [107]. Notably, this is increasingly true when other aspects are not considered: e.g., gender imbalance in the sample, missing socio-demographic analysis and details about the conditions under which the experiment takes place. When investigating the effect of stress, additional variability is linked to the non-specific response of humans in front of stressors [2], [35], requiring further attention for the experimental protocol design.

The analysis of the ground truth is certainly the trickiest part when stress is investigated. Except for the analysis of the CORT level, which requires either salivary, hair, urinary, plasma, serum, or sweat fingernails samples [26] and can not be performed in real-time [27], defining a reliable ground truth is not possible. For this reason, labelling the acquired data as either stressful or not would implicitly enhance a bias. As reported in [4], different approaches exist to label the data, conscious of the previous limitation: the results of the questionnaires and the occurrence of a stressful situation (e.g., a cognitive task), whether considered separately or together, can be used for this purpose. However, as previously noted, the experimenter should keep in mind the limitations of each questionnaire and the possibility that the user's response may not accurately reflect a stressful condition. This once again highlights the necessity of a reliable experimental protocol.

With this paper, which combines the efforts of researchers with different backgrounds, we want to provide the reader insights on how to induce and assess stress effectively by seeing the problem from technical and psychological perspectives. Hopefully, this would bring awareness of the different aspects that should be considered when studying and investigating stress, enhancing the quality of the experiments and reducing biases.

Nevertheless, the work is not free of limitations. We focused exclusively on common cognitive tasks as approaches to induce acute mental stress. However, this approach offers the advantage of allowing researchers to quantify cognitive impairment following induced acute stress. An additional limitation is that only hardware and practical approaches were analyzed to mitigate the effects of exogenous sources, whereas software solutions were overlooked. Indeed, addressing these would require separate work.

To conclude, the next subsections will be dedicated to some final remarks related to both stress induction and assessment.

### A. INDUCING STRESS

Designing a protocol that guarantees a stressful condition is fundamental, especially for all those studies that explore the effect of different treatments for stress reduction, e.g. through binaural beats [230], [231]. This is especially true if the CORT is not monitored. The great variability in subjects' stress response is a limitation in stress studies. Indeed, assuming a cognitive task to elicit enough stress in the candidates is not always correct. Note that this is true regardless of the task presented. For this reason, both personal and situational factors should be considered [49], [50], [51] to create a stressful event. The presence of an audience during data acquisition, a competition condition, rewards, punishments, evaluative conditions and no multiple attempts are approaches that the experimenter could adopt.

### B. ASSESSING STRESS

The stress assessment procedure starts with an in-depth analysis of the samples under investigation. The CORT level is influenced by several factors like phase of the day, hours of sleep, sex and pharmacological treatments, that if not considered, could bias the result of an experiment. Furthermore, if cognitive tasks are leveraged to induce stress in the participants, factors like education and age must be considered as inclusion or exclusion criteria.

Despite biases, questionnaires are useful to have a rapid response from the participants about their condition. It is preferable to fill out at least two questionnaires for assessing the level of stress (or anxiety) in the investigated sample, as suggested in [58]. Having a detailed screen of the participants about the psychological condition is pivotal for a study, and will guarantee homogeneity if comparison between independent groups is required. Some questionnaires are preferable to be presented before and after the experiments, whereas others like the visual analogue scale and the self-assessment manikin can be easily presented between tasks (if the protocol includes multiple acquisitions), because of their rapidity of response.

Besides the type of signal considered for stress detection, ranging from electrical to inertial measurements, it is important to analyze carefully the conditions under which the signals are collected and the sources of inaccuracy that would limit the quality of the data. If not, the collected data will be biased, limiting the generalization of a machine or deep learning algorithm. Devices used should guarantee comfort during the experiment and suitability for long-term measurements if the next step is to test the technology outside the laboratory. It is worth noting that solutions exploiting wires and attachable electrodes may be a confounding factor, eliciting a stress response [34] during the experiment. For this reason, comfort and miniaturized devices with low incisiveness should be considered if possible.

### C. FUTURE PERSPECTIVE

Emerging technologies such as Virtual Reality (VR) and Augmented Reality (AR) have a significant potential to induce acute mental stress. The realism is achieved through elements like place illusion, plausibility, and virtual body ownership [232], emphasizing VR's potential in psychological studies focused on stress induction and assessment. By designing laboratory experiments to replicate stress levels akin to those encountered in real-world settings [232], researchers may uncover previously unidentified stressors and novel psychological and physiological patterns in response to them, opening new research paths to be explored. Similarly, AR technologies can be adopted to simulate stressful situations in the real world, e.g., simulating a critical condition for training purposes [233], understanding the human response in personalized and crucial scenarios. Altogether, these technologies are set to become the new "controlled environment" for studying the effects of induced acute mental stress, most likely without the need for a physical laboratory in which to conduct the experiments.

Last but not least, particular attention should be given to chronic stress, which disrupts the immune system balance, causing peripheral and central inflammation, and contributing to various stress-related diseases [234]. Indeed, the increased cases of mental disorders in recent years require new approaches to monitor patients' emotional states, going beyond the traditional assessments typically used in a clinical environment [235]. In this context, VR, AR and smart sensors can play an important role. This is particularly true whether the combination of these systems is meant for telemedicine applications, which we believe will see widespread adoption in the coming years. The use of smart sensors like smartwatches, smart shoes and even smart mattresses [236] can be used for this purpose by monitoring the mental health of the patients toward personalized medicine, improving the quality of the treatments, or simply preventing the onset of a chronic stress condition.

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