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TOPICAL REVIEW

Study of the Acute Stress Effects on Decision Making Using Electroencephalography and Functional Near-Infrared Spectroscopy: A Systematic Review

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ABSTRACT This systematic review provides a comprehensive analysis of studies that use electroencephalography (EEG) and functional near-infrared spectroscopy (fNIRS) to investigate how acute stress affects decision-making processes. The primary goal of this systematic review was to examine the influence of acute stress on decision making in challenging or stressful situations. Furthermore, we aimed to identify the specific brain regions affected by acute stress and explore the feature extraction and classification methods employed to enhance the detection of decision making under pressure. Five academic databases were carefully searched and 27 papers that satisfied the inclusion criteria were found. Overall, the results indicate the potential utility of EEG and fNIRS as techniques for identifying acute stress during decision-making and for gaining knowledge about the brain mechanisms underlying stress reactions. However, the varied methods employed in these studies and the small sample sizes highlight the need for additional studies to develop more standardized approaches for acute stress effects in decision-making tasks. The implications of the findings for the development of stress induction and technology in the decision-making process are also explained.

INDEX TERMS Acute stress, electroencephalography (EEG), functional near-infrared spectroscopy (fNIRS), decision making.

I. INTRODUCTION

In recent years, stress has become a major concern, as it is affecting different groups of people. The COVID-19 pandemic has caused a rise of 25% in the prevalence of anxiety and depression worldwide, according to scientific research report published by the World Health Organization (WHO). The executive summary of this report listed the most impacted groups and outlined how the pandemic affected people's abilities to seek mental health care [1]. A study conducted in Malaysia during the COVID-19 lockdown in April 2020 found that of 716 adults, 70% reported stress, 76% reported anxiety, 42.3% reported depression, 29% actively handled stress, and 40% used humor as an escape from depression [2]. The implementation of movement control orders (MCOs) in response to the COVID-19 pandemic

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seriously impacted the mental health of working adults in the United Kingdom. According to data analysis from the Office of National Statistics, the prevalence of moderate-to-severe depression among working adults increased from 5.5%–7.5% before the pandemic to 18.0%–19.7% during the pandemic. In contrast, the depression rate among non-working adults did not fluctuate significantly, from 24.8% before the pandemic to 26.6% during the pandemic [3]. A study by researchers from three different universities surveyed 500 college students and found that their mean scores for depression, anxiety, and stress were 15.08, 18.24, and 19.02, respectively. The frequencies of depression, anxiety, and stress among the university students were 75%, 88.4%, and 84.4%, respectively. The findings of the study showed that the prevalence of depression ranged from normal (25%) to extremely severe (8.6%), that of anxiety ranged from normal (11.6%) to extremely severe (46.8%), and stress ranged from normal (15.6%) to severe (13.2%) [4], [5]. Stress is a major public health issue that can have a significant impact on both individuals and society. It can lead to increased healthcare costs, decreased productivity. The development of generalized, efficient, and robust emotion detection systems or stress detection systems is a promising area of research that has the potential to significantly impact the way we understand and manage stress [6]. These systems could help to identify people who are experiencing stress and provide them with the support they need. It could also help to prevent stress from becoming a more serious problem [7]. Acute stress can be conceptualized as the outcome of a cognitive evaluation or interpretation of a psychosocial stressor that exceeds an individual's coping capacity [8]. psychological stress was originally defined by pioneering theoretician, Hans Selye, as "the non-specific response of the body to any demand for change" [9]. stress is also utilized in various fields, such as mechanical systems and materials. Special controllers, like optimal controllers, are employed to regulate stress in these systems [10]. In humans the stress response is initiated when the amygdala perceives a threat through sensory input, resulting in increased activity of the amygdala [11], and activation of the hypothalamic–pituitary–adrenal (HPA) axis, a major hormonal system involved in the response to stress [12], [13], [14], [15]. The HPA axis plays a crucial role in preserving the homeostatic equilibrium by transmitting the central stress response to peripheral body systems [10]. In the long term, excessive activation of the HPA leads to an increase in heart rate and blood pressure [12]. The detection of acute stress among individuals can be accomplished using physiological signals acquired through various methods such as electrocardiograms (ECG) and galvanic skin responses (GSR). The integration of machine learning techniques and wearable technology in healthcare has the potential to significantly benefit society [16], [17]. Neurophysiological devices that utilize techniques such as electromyography (EMG), electroencephalography (EEG), electrocorticography (ECoG), and evoked potentials (EP) have been used to gain a deeper understanding of accurate and unblemished information in psychiatry. Other commonly used physiological sensors to study psychological responses include heart rate variability (HRV), functional magnetic resonance imaging (fMRI), and functional near-infrared spectroscopy (fNIRS) are also used to study the psychological response. Data from electrophysiological (e.g., EEG) and hemodynamic (e.g., HRV, fNIRS) sources may be pre-processed to extract relevant features such as stress level and cognitive load. To achieve better signal classification, the support vector machine (SVM) and K-nearest neighbor (KNN) algorithms are among the most commonly used machine learning methods for the classification purposes. Acute stress can have a significant impact on decision-making, including risk-taking. Although acute stress can sometimes lead to increased risk taking, it can also lead to more risk-averse decisions [18]. Recent review papers have shown that stress can alter decision-making. This is because stress affects the neural regions of the brain that are responsible for decision-making, such as the hippocampus, prefrontal cortex (PFC), ventrolateral prefrontal lobe, orbitofrontal cortex, anterior cingulate cortex, ventral striatum, and mesolimbic dopaminergic system [18], [19], [20]. In everyday life, we must weigh the importance of making quick decisions against the need for caution. This is known as the speed–accuracy trade-off [21]. When we are under stress, it is more likely that we make quick decisions, even if they are not appropriate. Previous research has demonstrated that exposure to acute psychosocial stress can influence ethical decision making; however, little is known about possible gender-based differences or the impact of personality on this phenomenon. A recent study found that stress increases arousal and negative emotions and negatively affects decision-making in different ways for men and women [22]. Additionally, other studies have examined the effects of stress in three phases, anticipation, reactivity, and recovery. Here, stress was induced by applying acute laboratory-based physiological stressors to healthy adults [23]. The impact of psychological stress and cortisol on decision-making in both healthy individuals and those with stress-related disorders can lead to negative outcomes that affect healthcare workers' attention, cognition, and clinical decision-making. This can have significant detrimental effects [24]. Decision making is an important process that is often conducted under stressful conditions. For example, in resuscitation situations, decision making is essential for saving lives [25]. Adolescents are particularly sensitive to stress when making decisions, which can lead to risky choices. The relationship between acute stress and decision-making is bidirectional. Thus, acute stress can affect the quality of decisions, and the decision-making process can evoke acute stress [22]. Previous studies have shown that acute stress can influence decision-making and risk-taking. However, the effect of acute stress on decision making varies depending on the context. For example, when decisions provide little or no probabilistic information (i.e., are ambiguous), stressed females may be more risk-averse and males may be more risk-seeking [26], [27], [28]. In addition to acute stress, other factors can influence decision-making. These factors include intuition, personal traits, and relationships. Perception also plays a role in decision making, as it can affect self-esteem, confidence, self-worth, value, and equity [29]. Despite the extensive research on the psychological impacts of stress, there remains a crucial gap in understanding the specific neurophysiological responses to acute stress during decision-making processes. This gap highlights the need for a systematic review that not only synthesizes the existing literature on the impact of acute stress on decision-making but also examines the potential of neurophysiological techniques, such as EEG and fNIRS, to provide insights into the brain mechanisms affected by stress. Addressing this gap is essential for developing targeted interventions that can mitigate the adverse effects of stress on decision-making, particularly in high-stress situations such as those experienced during the COVID-19 pandemic. Thus, this review aims to bridge this gap, offering a comprehensive analysis that could inform future research directions and intervention strategies. Answering the following questions was the main aim of this systematic review:

- How does acute stress affect decision-making in various stressful conditions?
- Would EEG and fNIRS be able to detect the effect of acute stress on decision making, and what are the available validation methods?
- What is the latest computational method used to extract and classify EEG and fNIRS data?

The answers will help readers broaden their understanding of current research on the subject, providing a comprehensive summary of the numerous emerging experiments, issues, and themes. The remainder of this paper is divided into six sections. The background of acute stress, decision-making, acute stress induction techniques, and physiological measurements is covered in the following section. The third section outlines the methods used to carry out the systematic review processes. The results are presented in the fourth section, and a discussion is reported in the fifth section. The limitations and future direction are presented in the sixth section, and finally the conclusion of this systematic review is presented.

II. BACKGROUND

A. ACUTE STRESS

Selye, a pioneer in stress research, first conceptualized stress as "the non-specific response of the body to any demand for change" [30]. Acute stress can affect cognition in several ways, acting rapidly via catecholamines, and more slowly via glucocorticoids. Catecholamines act through beta-adrenergic receptors and the availability of glucose. They produce rapid changes in cognition such as increased attention and arousal. Glucocorticoids elicit biphasic modulation of synaptic plasticity over time and induce enduring alterations in dendritic structures that persist for weeks. They can have both positive and negative effects on cognition depending on the dose and duration of exposure. Prolonged stress exposure can lead to neuronal loss, particularly in the hippocampus. The hippocampus is an important brain region involved in memory formation. Recent investigations have indicated that cognitive impairments related to glucocorticoids and stress, particularly those affecting declarative memory, are likely linked to their impact on the hippocampus. Declarative memory is a type of memory that involves the conscious recollection of facts and events. The acute effects of stress on emotionally laden memories are hypothesized to involve other structures such as the amygdala. The amygdala is an important brain region for emotional processing [31]. Acute stress is a fundamental construct in biology and is broadly used in various applications, such as the psychological, physiological, social, and environmental domains. Within fMRI settings, numerous paradigms have been developed for the patterns triggered by acute stress. However, the existence of a global brain activation pattern specifically linked to psychosocial stress remains uncertain [32]. Originally defined by Selye [9], the concept of stress transcended its former confinement to the acute activation of the hypothalamic–pituitary–adrenal (HPA) axis and subsequent sympathoadrenal responses to homeostatic disturbances. Contemporary understanding acknowledges that stress responses extend even to lower organisms and individual tissues and cells [33]. Notably, as the concept of homeostasis has been refined, the notion of stress has undergone concomitant specification. For instance, oxidative stress pertains specifically to disruptions in redox signaling and control [34], whereas endoplasmic reticulum stress denotes the strain induced by the accumulation of unfolded proteins in the endoplasmic reticulum [35]. Broadening the concept of homeostasis has facilitated the pervasive incorporation of stress into various aspects of our culture, making it a fundamental principle in the fields of biology, medicine, and neuroscience. Its versatile applications have been utilized in the examination of psychological, physiological, social, and environmental phenomena. Subsequently, after extensive research, Selye proposed a dichotomous categorization of stress into "eustress," signifying beneficial stress, and distress, representing harmful stress [36] Despite this refinement, many researchers continue to adhere to Selye's "General Adaptation Syndrome" (GAS) framework to define stress and interpret it as a potential threat to health. The continuing divergence in conceptual interpretations in scientific discourse highlights the complexity of stress as a multidimensional phenomenon.

B. DECISION MAKING

Decision making is a complex process involving the collaboration of several brain systems. The PFC, amygdala, and basal ganglia are important in decision-making [37]. The PFC gathers and evaluates information, the amygdala processes emotions, and the basal ganglia executes decisions [27], [38].

For example, when you see someone waiting to cross the street, you quickly identify whether it is your spouse, boss, or a stranger, and respond accordingly. However, in a rainstorm, it is more difficult to gather information about a person owing to increased noise, and a longer period of observation is required before deciding on a course of action. This occurs because noise can make it more difficult for the PFC to identify a person and can also increase the emotional salience of the situation, which can lead to a fear response from the amygdala. Decision-making is a complex subject that has been extensively explored in various branches of psychology. It encompasses a broad range of choices, drawing inferences to select the most advantageous option, and spans the continuum from uncertainty to certainty [18]. Men tend to exhibit riskier decision-making than women in real-life situations, and the role of stress in influencing this sex difference remains a topic of ongoing debate [39]. During adolescence, peer influence plays a critical role in shaping decision-making, impacting health-compromising risky behaviors, and positive psychosocial outcomes such as learning, exploration, and prosocial behavior [40].

C. STRESS INDUCTION AND DECISION-MAKING METHODS

The Trier Social Stress Test (TSST) is a well-established laboratory-based stress protocol used for more than three decades to elicit acute stress responses in participants. This test comprises a 5-min simulated job interview, followed by a 5-min mental arithmetic task, both conducted under evaluative conditions. Extensive research has confirmed that the TSST effectively activates the hypothalamic–pituitary–adrenocortical (HPA) axis and other stress-mediating systems [41]. In recent years, various adaptations of the TSST have emerged, broadening its applicability. These adaptations include the "placebo TSST" [42], the "friendly TSST" [43] and the group version (TSST-G), which was developed to accommodate stress induction in a collective setting [44]. In addition, a virtual reality version (TSST-VR) was created by incorporating immersive technology to simulate stress-inducing scenarios [45]. Researchers have also adapted the TSST to be used with children and have explored its implementation online, resulting in an Internet-delivered TSST (iTSST). The iTSST demonstrated efficacy in inducing acute stress responses in participants, as evidenced by the observed decrease in the root mean square of successive difference (RMSSD) and an increase in heart rate in various tasks, from resting to delivering a speech [46], [47]. Another way of inducing stress is the Montreal Imaging Stress Task (MIST), which is used to study the effects of stress on decision-making. The participants in the MIST face a series of financial decisions involving potential gains and losses. Each decision has a fixed probability of success or failure, and the participants are asked to choose the option they believe would result in the greatest financial gain [48]. One decision-making approach that has been studied in the context of MIST is reference-dependent decision-making, which involves using a reference point or benchmark to evaluate options. For example, some studies have found that individuals tend to be more risk averse when the reference point is a loss and more risk seeking when the reference point is a gain. This suggests that reference points can influence how individuals weigh the potential risks and rewards of different options, and how they make decisions in stressful situations [49]. The effects of acute stress on cognitive and emotional functions were investigated using the cold pressor test as a psychological induction technique. The test involves immersing one hand of the participant in cold water (typically around 5–10 °C) for a set period, usually 1–3 min. Cold water serves as the physical stressor, and participants' physiological and psychological responses to the stressor were measured [50]. The Stroop induction task is a commonly used cognitive task that involves presenting individuals with a list of words that are printed in colors that do not match the words themselves (e.g., the word "red" printed in blue ink). This task requires individuals to name the color of the ink rather than the word itself. This task can be modified to induce stress in individuals by adding time pressure or other stressors, leading to a variety of effects on decision making [51]. According to other research, stress may make people more cautious in their decision-making because they may select safer alternatives to relieve their stress [52].

D. OBJECTIVE AND SUBJECTIVE MEASUREMENT

EEG is a common choice for brain–machine interface applications because it is relatively affordable, has high temporal resolution, and is compatible with a variety of devices. EEG has several advantages over other brainwave measurement techniques, such as ECoG and magnetoencephalography (MEG). First, EEG is noninvasive, which means that it does not require electrode insertion into the brain [53]. Second, EEG has a high temporal resolution, which means that it can be used to measure changes in brain activity over very short periods. Third, EEG is compatible with a variety of devices, which means that it can be used in a wide range of brain–machine interface applications [54]. However, EEG has some limitations. First, EEG has relatively limited spatial resolution, which means that it cannot be used to precisely localize brain activity. Second, EEG is susceptible to various artifacts such as muscle activity and eye movement. These artifacts make it difficult to interpret EEG data.

fNIRS is a relatively new technique that uses light from the near-infrared range to measure changes in the levels of oxygenated and deoxygenated hemoglobin in the brain [55]. Although it has been used for studying brain blood flow for over 20 years, its use in brain–computer interfaces (BCIs) are relatively recent, dating back only a few years [56]. The feasibility of fNIRS for BCIs has been demonstrated [57], [58]. The motor cortex and PFC are good candidates for fNIRS-BCI applications. The motor cortex allows for the natural control of external devices through the BCI. The

PFC is also a suitable option because it contains fewer motion-related artifacts and signal weakening caused by hair movement [59].

III. REVIEW METHOD

A. SEARCH METHOD

This systematic review followed the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines [60], [61] also followed the PRISMA checklist to ensure a comprehensive and transparent reporting of the synthesis process. the included studies were searched for English-language literature on the effect of acute stress on decision-making. The search terms included combinations of subject headings (/) and keywords ("") [("Acute stress" OR "stress*" OR "mental stress") AND ("decision making" OR "Decision") AND ("functional near-infrared spectroscopy" OR "FNIRS" OR "electroencephalog*" OR "EEG")]. The process is presented in Figure 1. The search was conducted using PubMed, PsycINFO, IEEE, Web of Science, and Scopus. Only full-text articles published between 2014 and 2023 were included.

B. STUDY SELECTION CRITERIA

In this systematic review, all the acquired articles underwent a two-step screening process, starting with a review of the title and abstract, followed by a thorough examination of the full text. Any disagreements regarding the inclusion and exclusion criteria were independently examined by two authors (A.A and N.K) and then resolved through consensus discussions. The studies selected for inclusion in this review focused on unmedicated healthy adolescents and adults, aged 15 years and older, with no history of neurological or psychiatric disorders. These individuals were subjected to acute laboratory psychological stressors, and their brain activity was measured using EEG or fNIRS. Additionally, studies investigating specific populations (e.g., psychiatric patients) or interventions (e.g., pharmacological interventions, meditation) were considered for inclusion if they featured a control group that met the criteria, and the data for the control group were reported separately. To maintain the academic rigor of this review, certain types of publications were excluded, including review articles, meta-analyses, conference proceedings, editorials, letters, case reports, and non-peer-reviewed articles. Furthermore, conference abstracts were excluded from this review. The timeframe for inclusion was limited to articles published between 2014 and 2023, with the final date of inclusion being August 31. Table 1 summarises the inclusion and exclusion criteria for this systematic review.

C. DATA EXTRACTION

The primary author extracted and double-checked data from the included articles. The extracted variables encompassed various aspects, including population demographics. This involved recording information such as sample size, mean age, and the inclusion and exclusion criteria used in participant selection. The experimental category covered details related to the study design, stressors and decision-making tasks, objective and subjective measurement methods, and data analyses. In addition, the control condition implemented, the cover story presented to participants, and any specific timing considerations contemplated during the study were recorded. Information about the number of channels used in EEG and fNIRS and placement positions of the fNIRS optodes and EEG electrodes was obtained. The specifications for the EEG analysis included documenting the low pass frequency, high pass frequency, and the procedures employed for artifact removal during the EEG data analysis. Various physiological measurements were collected including alpha-amylase, cortisol, heart rate, HRV, electrodermal skin activity (EDA), blood pressure, respiratory rate (RR), and responses to state questionnaires. Additionally, the significant changes observed in these studies were recorded. Through this comprehensive data acquisition process, this review aims to provide a comprehensive analysis of the relevant studies' methodologies and results in the context of psychosocial stressors and brain activity measured using EEG and fNIRS.

TABLE 1. Summary of inclusion and exclusion criteria.

Criteria	Inclusion	Exclusion
Publication Year	2014 - 2023	Articles published before 2014 or after August 31, 2023
Subjects	Unmedicated healthy adolescents and adults, aged 15 and older	Subjects with a history of neurological or psychiatric disorders
Interventions	Acute laboratory psychological stressors	Pharmacological interventions, meditation (unless with a control group meeting the criteria)
Measurement Methods	EEG or fNIRS	Studies not utilizing EEG or fNIRS
Study Type	Full-text articles	Review articles, conference proceedings, editorials, letters, case reports, non-peer reviewed articles, conference abstracts
Specific Populations	Studies with specific populations (e.g., psychiatric patients) if featuring a control group that meets criteria	Studies without a relevant control group
Data Reported	Studies where data for the control group were reported separately	Studies not reporting data for control groups separately

IV. RESULTS

In total, 588 studies were initially identified. Among these, 248 papers were excluded based on criteria such as full-text availability in English language and relevance to human subjects. After removing duplicate entries using Microsoft Excel, the resulting count of distinct articles was 192. Subsequently, a thorough assessment of titles and abstracts led to the elimination of 133 additional papers. The remaining 59 studies were evaluated against the inclusion and exclusion criteria. Upon closer examination of the full texts, 39 papers were excluded, resulting in the final selection of 27 papers for research analysis. Figure 2 shows the number of publications by year between 2014 and 2023. This section explains

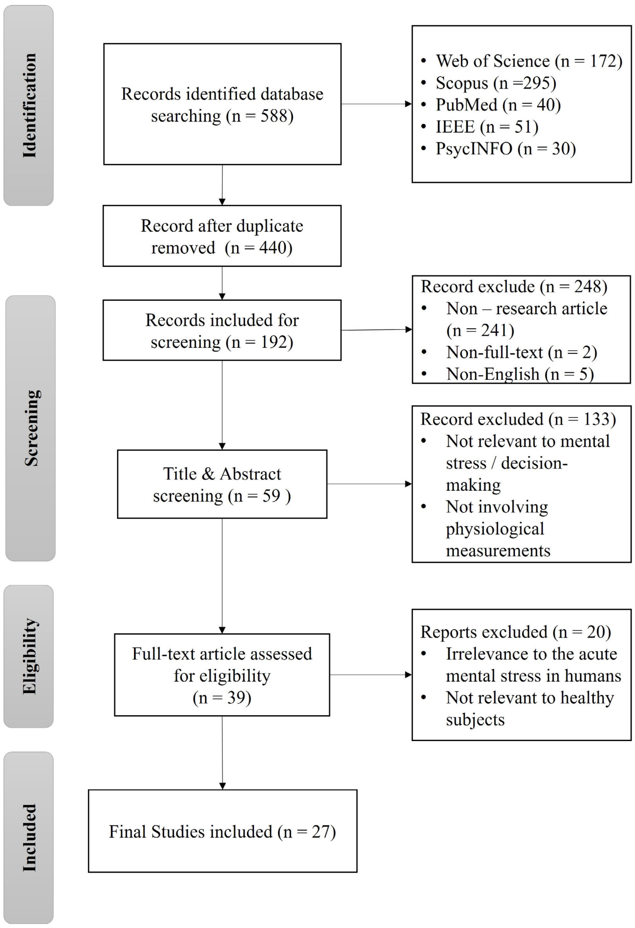

FIGURE 1. Flow of information in accordance with the preferred reporting items for systematic review and meta-analysis (PRISMA) guidelines.

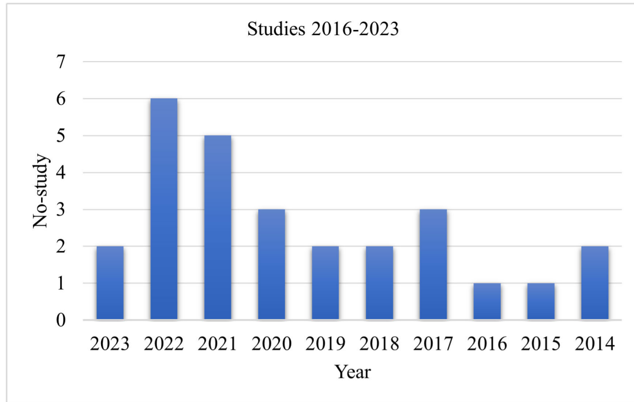

FIGURE 2. Included studies by year of publication, from 2014 to 2023 (August).

the experimental design, followed by the physiological and subjective measurement methods, and finally, data analysis and processing techniques. The experiment design comprises the study population and stressor techniques used to induce acute stress. The physiological measurement methods include all neurophysiological and imaging devices, such as EEG and fNIRS. The subjective measurement methods include the questionnaire and other self-assessment concepts. Data analysis comprises pre-processing and feature extraction, followed by machine learning and classification techniques.

A. RISK OF BIAS ASSESSMENT OF THE INCLUDED STUDIES

In the evaluation risk of bias, the Cochrane risk of bias tool [62] and the revised tool for assessing risk of bias in randomized trials (ROB 2.0) [63] were employed, both of which are specifically designed for the examination of bias risk. The studies were independently examined by two authors (A.A and N.K) across five principal domains where bias might manifest. Following individual assessments, discussions were held to reach a consensus on the findings. This rigorous examination process entailed the review of 27 articles, among which 2 were identified as having a high risk of bias and 9 as presenting some concerns. It is noted that articles assessed to have a low risk of bias were not included in the summary table, a practice consistent with other systematic reviews [25]. Table 3 shows the risk of bias for the studies identified as having a high risk and those with some concerns.

B. EXPERIMENT DESIGN

After including 27 studies in this systematic review, different types of experimental designs and different setups were identified. In this section, we explain the mainstream task categories and setups. In a stressor task experiment, the goal is to expose participants to a stressor to study the effects of stress on various outcomes such as brain activity, cognitive function, and performance. The design of the experiment depends on the specific research questions being asked and the outcomes in which the researchers are interested. The design of a stressor task experiment could include various components, such as personality testing, cognitive tasks, and other performance measures. Additionally, the study may involve multiple stages, such as data collection, pre-processing, and analysis, to ensure that the results are reliable and accurate. Table 2 summarizes the characteristics of the included studies.

C. STRESSORS AND DECISION-MAKING TASKS

A stressor task is an activity that causes both stress and anxiety. Stressor tasks can vary greatly in nature and intensity, but some common examples include meeting tight deadlines, giving presentations, taking tests, and dealing with difficult or demanding people. Stressor tasks can be triggered by external circumstances or events, or they may arise from within an individual because of personal goals or expectations. Coping with stressors often involves finding ways to manage and reduce the stress and anxiety they create through techniques such as time management, relaxation, or seeking support from others. In a study [70] the subjects had to perform mental arithmetic, auditory monitoring, visual monitoring, and

TABLE 2. Study population, measurement methods, and machine learning algorithms of recent studies.

Study	Participants	Age	Stressor & Decision-Making Task	Measurement Methods	Analysis Method	Area of Interests
[64], 2023	198	35 ± 20	Lucky Door	EEG	Block-Sparse Bayesian learning (SBL) & Robust Linear Regression & T-test & ANOVA & Tukey–Kramer post-hoc & linear mixed models	Para hippocampal & entorhinal
[65], 2023	67	20-70	go/no-go & N-Back & Verbal Fluency	fNIRS	Binomial logistic regression & Spearman's rho & U-Test	Frontotemporal
[66], 2022	24	$19-24$	TSST BART	fNIRS	JCCB-FSC Sparse & 3rd order band-pass filter & modified Beer-Lambert	Prefrontal Cortex
[67], 2022	5	$21-23$	Surgical endoscope simulator	fNIRS	Low-Pass Filter & ANOVA	Prefrontal Cortex
[68], 2022	51	$15-39$	TSST P-TSST Lexical-decision task	EEG & salivary Alpha amylases	Post-Hoc Tests & ANOVA & T-Test	Corpus Callosum
[69], 2022	33	/	VR Simulation for Electrical Construction	fNIRS	Bandpass filter & Beer-Lambert Law & Shapiro-Wilk's normality test & General Linear Model (GLM)	Dorsolateral Prefrontal Cortex (DLPFC) & Prefrontal Cortex
[70], 2022	20	29 ± 5	Mental Arithmetic Immersive driving simulator	EEG & SC & NASA-task load index	REBLINCA Method & Multi-channel Wiener Filter (MWF) & Band-pass filtering	Parietal Lobes
[71], 2022	85	$21-60$	perceptual decision-making scenario & BART	EEG & ERP	Band-pass filter & ICA & Event-Related Potential (ERP)	Parietal-Occipital
[72], 2021	20	$18-30$	Fish police	EEG & Pulse Rate Measurements	Welch's power spectral density estimation & Arterial Pulse Variance Measurements	Cerebral Cortex
[73], 2021	39	30 ± 3	Sound Clips	FNIRS & HRV	Butterworth band-pass filter & Modified Beer-Lambert Law & Sliding Window Correlation SWC & Dynamic FC & RF	PFC & Temporal Lobes
[74], 2021	84	21 ± 2	Iowa Gambling Task (IGT) & TSST_G	fNIRS & salivary Alpha-Amylases (sAA)	T-Test & ANOVA & MDL	Prefrontal Cortex & Left Temporal Lobe
[75], 2021	83	$19-29$	BART TSST	EEG & salivary alpha-amylases & HR	Ocular artefact reduction & Low-pass filter & Bonferroni test & ANOVA & PANAS	Frontal lobe & Parietal lobe & Occipital lobe & Temporal lobe
[76], 2021	27	23 ± 5	Newsvendor Problem (NP)	FNIRS	Band-pass filter & GLM	DLPFC & orbitofrontal cortex (OFC) & Frontal Polar Area (FPA)
[77], 2020	20	25 ± 2	Mathematical questions & Montreal Imaging Stress Task (MIST)	fNIRS & HRV	Band bass filter & Independent component analysis (ICA) & Contingent Negative Variation (CNN) & SVM & DNN & RF	prefrontal cortex (PFC)
[78], 2020	16	/	VR factory shutdown	fNIRS & Eye tracker	Approximate Entropy (ApEn) & Beer Lambert law & Bnd-pass filter & Kurtosis wavelet & DT & RF & KNN & LR & NB	L/RDLPFC & L/R Premotor Cortex & L/R Primary Motor Cortex
[79], 2020	15	32 ± 12	Go/No-Go game	EEG	Zero-Phase Shift Butterworth Filter & Passband & Hanning Window & Notch Filter	Frontopolar &L/R Anterior Frontal & L/R Temporal Parietal
[80], 2019	81	22 ± 1	Moral questions	fNIRS & Survey	Modified Beer-Lambert	DLPFC
[81], 2019	41	$18-55$	Driving situation	EEG	ERSP & ERP & ICA & PLV & ANOVA & (GLM-fit) & Low-Pass Filter	Frontal & Temporal & Parietal & Occipital Lobe
[82], 2018	40	25	Virtual Group Setting	EEG & Survey	FFT & Spectral Power Across & Bonferroni-Corrected & Low Pass Filter & Hanning Window	PFC
[83], 2018	50	$19-39$	linguistic ambiguity in English (foreign) sentences	EEG & ECG & HRV	Bandpass Filter & FFT Based Welch's Periodogram & ICA	Parieto-Occipital
[84], 2017	4	35 ± 9	Indoor & outdoor Physical activity	EEG & ECG & BP & RR & SpO2	Expectation Maximization (EM) & SVM & RM & DT	Frontal & Temporal & Parietal & Occipital Lobe
[85], 2017	36	37 ± 11	Stroop test & Mini-Mental State Exam	EEG & MMSE	Butterworth IIR Bandpass filter & Fast Fourier Transform & Principal component analysis (PCA)	Frontal Parietal

TABLE 2. ***(Continued.)*** **Study population, measurement methods, and machine learning algorithms of recent studies.**

[86], 2017	100	$25-92$	Balloon Analog Risk Task (BART)	fNIRS	Band-Pass Filter & Spectral Decomposition & GLM-Fitting & ANOVA	Middle Frontal Gyrus (MFG) & DLPFC
[87], 2016	11	/	Balloon Analog Risk Task (BART)	FNIRS & EEG & HR & Bp & sAA	Bandpass Filter & Modified Beerlambert Law & Spatially Resolved Spectroscopy (SRS) & F-Test & Bonferoni Post-hoc Test & Tukey's Correction & GLM & ANOVA	PFC
[88], 2015	17	23 ± 3	Imagination of Risky Scenarios	EEG & Blood Pressure	High/Low Pass filter & Fast Fourier Transform & Correlation/Mediation and Moderation analysis & Likelihood ratio test & ANOVA	Frontopolar & Occipital & Parietal Lobe
[89], 2014	25	$17-25$	Random Dot Motion Task	EEG	Post-Hoc Tests & Band-Pass & Law Pass Filtering & Linear Mixed Effects (LME) & General Additive Models (GAMs)	Frontal & Temporal & Parietal & Occipital Lobe
[90], 2014	61	$18-40$	Gambling task	EEG & EOG	Post-Hoc Tests & Bonferroni & ANOVA	Frontocentral & Temporal & Parietal & Occipital Lobe

TABLE 3. **Summary of the risk of bias assessment of the included studies.**

Study	Risk of bias arising from the randomisation process	Risk of bias due to deviations from the intended interventions	Missing outcome data	Risk of bias in measurement of the outcome	Risk of bias in selection of the reported result	Final risk of bias assessment
[67], 2022	Low	Low	Low	Some	Low	Some Concern
[70], 2022	Low	Some	Low	Low	Low	Some Concern
[72], 2021	Low	Low	Some	Low	Low	Some Concern
[76], 2021	Low	Low	Low	Some	Low	Some Concern
[78], 2020	Low	Low	Low	Some	Low	Some Concern
[79], 2020	Low	Some	Low	Low	Low	Some Concern
[81], 2019	Low	Low	Some	Low	Low	Some Concern
[82], 2018	Low	Low	Low	Some	Low	Some Concern
[83], 2018	Low	Low	Low	Some	Some	High Risk
[84], 2017	Some	Low	Some	Some	Low	High Risk
[87], 2016	Low	Low	Some	Low	Low	Some Concern

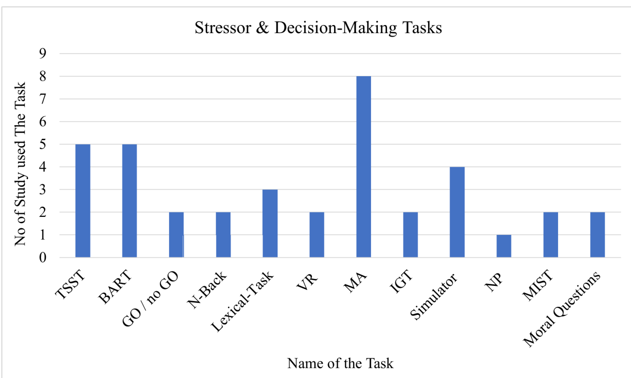

FIGURE 3. **Stressor and decision-making tasks.**

phone number entry tasks all at the same time and separately to observe the different outcomes [68], [74], To mitigate the impact of the order, participants were randomly allocated to different sessions, with 50% experiencing the affective stimuli during one instance [73], Figure 3 shows some of the most commonly used decision-making tasks.

1) TRIER SOCIAL STRESS TEST (TSST)

TSST is a standardized laboratory stressor task used to induce psychological stress in research participants [66], [68], [74], [75]. It was designed to simulate the stressors that people encounter in their daily lives, such as public speaking or job interviews. Over the years, the TSST has been developed and modified, and different versions are now available. The placebo-TSST is used as a control condition in research studies that aim to investigate the effects of stress on various outcomes, such as physiological responses or cognitive performance. By comparing the effects of the TSST with those of the placebo-TSST, researchers can determine whether the observed effects are specifically due to the stressor task or whether they are due to other factors [68]. The Trier Social Stress Test for Groups (TSST-G) is a variant of the TSST designed to be administered to groups of participants rather than to individuals. It is similar to the standard TSST in that it comprises three stages: preparation, speech, and mental arithmetic. However, in the TSST-G, the speech and mental arithmetic tasks are group-oriented, and the evaluators provide feedback to the group rather than to individual members [91]. The TSST-G is often used in research on group dynamics and social support, as well as in studies on the effects of stress on group performance and cohesiveness. It is a useful tool for studying how group members cope with stress and support each other in stressful situations [74]. Other variants of the TSST include the online version of the TSST and the virtual reality TSST.

The TSST consists of three stages, as follows. Preparation: Participants are given a speech, which they can prepare during 5 min. Participants are told that they will have to deliver the speech in front of a panel of evaluators. Speech: Participants are asked to deliver their prepared speech for 5 min in front of a panel of evaluators who were trained to be critical and unsupportive. Mental arithmetic: Participants are then asked to perform a mental arithmetic task (usually subtracting in steps of 17) in front of the evaluators (10 min), who continue to be critical and unsupportive. The TSST is a widely used stressor task because it is relatively easy to administer, and it has been shown to reliably induce stress in a large proportion of participants. It is often used in research on stress, anxiety, and other psychological phenomena.

2) BALLOON ANALOGUE RISK TASK (BART)

BART is a psychological assessment used to gauge human risk-taking tendencies and decision-making aptitudes [87],This task employed a virtual balloon displayed on a computer screen that participants could inflate by pressing a button. When the button is pressed, the balloon expands incrementally, leading to a monetary gain for the participant. However, there is a risk involved because if the balloon bursts, all the accumulated earnings will be forfeited [66]. A modified version of the BART using the same experimental materials was introduced by Fein and Chang [92]. The distance between the participant' seat and computer screen were 100 cm. Each trial of the modified BART began with a fixed red point displayed for 1,000 ms, followed by the simulation of a red balloon (with dimensions of 3.0 * 3.5 visual angles). The current number of rounds and related scores are shown below the balloon. Participants can select either the "F" or "J" key on the keyboard when the request "please decide" appears inside the balloon. This provides them with the opportunity to inflate the balloon or wrap up the trial early and gather the final scores. Crucial assignments (inflate/cash out) are distributed evenly among the participants and the decision time is unlimited. The number of pumps reflects the risk-taking behavior of a participant. The BART task used [71] to represent the intrinsic factors that could affect the participants' hazard recognition strategies. In accordance with the methodology outlined in [86], the data collection process is divided into four phases: tallying the total counts of balloons resulting in winnings and losses, calculating the average -adjusted pumps/inflations per balloon (excluding loss-associated balloons), and mining the average -adjusted pumps/inflations per balloon (excluding win-associated balloons).

3) IOWA GAMBLING TASK (IGT)

The IGT is a crucial psychological method for assessing a person's ability to make decisions. The IGT is an engaging evaluation created by Antonio Damasio and his colleagues at the University of Iowa in the 1990s. The participants use four card decks, named A, B, C, and D. These decks contain a mix of cards that can result in profits or losses of money. Participants are given the task of choosing a card from one of these decks, and then they are given feedback detailing the financial results of their decisions [93]. The study [74] used fNIRS in conjunction with the IGT to determine how acute stress affected the choices made by female dyads. In this method, participants are given a deck of cards labeled A, B, C, and D. The participants are required to choose a card from the deck for each trial. The dyad members were told that the awards would be split equally. Notably, the findings showed that in the experimental setting, women experiencing acute stress showed a heightened tendency to make logical decisions. Researchers can learn from this study about how stressed dyads may develop enhanced cooperation and increased brain-to-brain connections. In [90],participants performed a gambling task under both control and stress conditions. The task involved choosing between two options, one of which was more likely to result in a gain, and the other in a loss. The participants were instructed to maximize their gains and minimize their losses. This task was designed to measure feedback processing in the brain, specifically feedback-related negativity (FRN) and feedback-related changes in theta and beta oscillatory powers.

4) THE N-BACK RECALL TASK

The N-back task is a cognitive task used to assess the working memory. Working memory capacity refers to the cognitive ability to store and manipulate information temporarily, in the short-term memory. It is often used as a measure of the executive function, which is a set of cognitive processes involved in controlling and coordinating other cognitive processes, such as planning, problem-solving, and decision-making. In the 3-back recall test, participants are presented with a series of stimuli (e.g., letters or numbers) on a computer screen and asked to recall the stimulus presented three stimuli before [94]. For example, if the stimuli presented as "A B C D E," the participant would be asked to recall the letter "B" on the third trial. In a recent study, participants were asked to judge whether the present shape resembled that displayed at a specific position earlier in the sequence after being given a series of randomly generated shapes. After a 2.5-sec break, the shapes reappeared in black on a grey background for 500 ms each one. If the shape matched, the participants were instructed to swiftly hit a particular key; otherwise, no action was required. For analysis, data on response speed and accuracy (measured in milliseconds) were collected [65].

5) THE LEXICAL DECISION TASK (LDT)

In the LDT, participants are presented with a string of letters and asked to determine whether the string forms a word or a non-word as quickly as possible. This task is often used to study various aspects of language processing including reading and lexical access. Stress is not typically a factor in a lexical decision task [95],because the task does not involve any emotional or physical demands on the participant. However, it is possible that the level of stress or anxiety of the participants could affect their performance on the task performance, as these factors can have an impact on cognitive function and attention. In a study [68], participants were required to determine whether a given stimulus was a real word or a nonword; the stimuli consisted of 80 German nouns and 80 combinations of letters that were pronounceable but without meaning. In another study [83], participants completed an English language test in which they had to answer 106 statements, 52 of which had many alternative meanings. The participants clicked the left or right button on a computer mouse to indicate whether the sentences presented on a screen can be comprehended in a single way or a variety of ways. Based on their research, they hypothesized that stressful conditions might also affect the synchronization of brain waves in the frontal and temporal areas, particularly in the theta and alpha frequency ranges. The relationship between resting HRV and brain oscillatory activity during cognitive control was highlighted by this condition, along with any potential sex differences in this interaction.

6) THE MONTREAL IMAGING STRESS TASK (MIST)

The MIST is a standardized experimental stressor used in research studies to induce stress in healthy individuals [77]. It is designed as a controlled and standardized method of exposing individuals to stressors that can be used to study the effects of stress on various aspects of physiology, cognition, and behavior. The MIST consists of a series of tasks designed to be cognitively and emotionally challenging. These tasks may include public speaking (e.g., the TSST task), mental arithmetic, or difficult computer tasks [96]. The MIST also included a control condition in which individuals were asked to perform a simple task that was not stressful. The MIST has been used in several research studies to examine the consequences of acute stress on decision-making and various aspects of physiology and behavior, including cardiovascular function, cognition, and emotion. It has also been used to study the effectiveness of different stress-reduction interventions, such as mindfulness training or relaxation techniques, in reducing the negative effects of stress. A study by [79], used a stress go/no-go task, a type of cognitive task used to measure attention, impulsivity, and response inhibition. Firefighters were asked to complete a job in a laboratory setting while wearing firefighting gear and while not wearing it (the decision was random), at a temperature of 25 to 26 °C. Following the exercise, the participants completed a go/no-go task. Notably, when subjects wore firefighting gear, there was a noticeable rise in incorrect answers, whereas no such change was observed in the absence of gear. Additionally, an examination of frontal EEG data indicated a reduction in theta power when comparing the values before and after the exercise, specifically when participants wore firefighting gear; this change was not observed in the absence of firefighter gear.

7) STROOP COLOR WORD TEST (SCWT)

The SCWT is a task used in psychology research to measure an individual's ability to process and inhibit conflicting information. It is often used to assess cognitive control, which is the ability to regulate thoughts, emotions, and behaviors to achieve a specific goal [85]. In the SCWT, participants are presented with a list of words printed in different colors (Stroop [110]), [97], some of which match the color of the ink, for example, the word green written in green ink, while others do not (e.g., the word green written in yellow ink). In a study conducted by [98], the brain waves of tennis players were recorded while they rested for 60 s. They then participated in a single SCWT practice session. The official test protocol consisted of the following steps: the SCWT, mental arithmetic, and mental arithmetic, followed by a blank screen with the participants in a calm resting state. Data on the brainwaves of 25 regularly trained players were collected. Data from one subject were eliminated owing to insufficient information, leaving 4433 records from the remaining individuals. Additional stress-related characteristics were included in the analysis and classified as high, medium (mid), or low stress levels in accordance with the experiment.

8) MENTAL ARITHMETIC TASK (MA)

The MA is one of the most common tasks used in psychological research to measure an individual's ability to perform basic arithmetic calculations quickly and accurately. It is often used as an indicator of how quickly cognitive tasks are processed, that is, the speed at which an individual can perform mental tasks. To complete the MA, each participant is presented with a series of arithmetic problems and asked to solve them as quickly as possible. These problems involve both simpler calculations, such as addition, subtraction, multiplication, and division, and more complex calculations, such as finding squares or square roots. A time limit for completing the task is typically given to the participants, and their performance is scored based on the number of problems that they could solve correctly within the time limit. In the MA test used in [98], addition, subtraction, multiplication, and division were displayed with numbers ranging from 1 to 1000, appearing at intervals of 5 s. In [70] the MA was combined with other tasks for multitasking purposes, and as the MA difficulty increased, the quantity of digits (ranging from 1 to 3) and the number of carryover digits (ranging from 0 to 2) progressively increased. In a related study [77], [96] the MA was employed for a task lasting 30 s involving the solution of mathematical questions.

9) DILEMMA SCENARIO

A dilemma scenario involves two or more operations, each of which has its own advantages and disadvantages. These situations can cause stress because they require attention to make decisions, often under pressure, and with limited information. Dilemma scenarios can be challenging because they often involve trade-offs and difficult choices, and it can be difficult to determine which option is the "best" one. The train and footbridge conundrum were used in early research [80], [81]. In this dilemma, a choice must be made as to whether to pull the lever to swerve the train away from five people on the track. By pulling the lever, the train is steered to a footbridge with one person present. The pedestrian is saved if the lever is not lifted, but then the five people on the track are in danger. The second study examined how decision-making is affected by time constraints and tracked the brain activity of morally responsible people as they addressed ethical dilemmas. The conclusions covered the moral decisions of 43 participants Under the conditions of time constraints, 4 of 21 subjects made moral choices. Conversely, when given ample decision time, 11 participants (50%) made morally aligned choices. The results were analyzed using chi-square tests, which revealed a marginally significant relationship between time constraints and decision making (p = 0.056) [80].

10) VIRTUAL AND MIXED REALITY (VR & MR)

Virtual reality (VR) has the potential to be a useful tool for studying the effects of acute stress on decision making. Researchers can create scenarios that simulate real-life stressors in virtual reality environments. Several studies have found that VR can successfully mimic real-life stressors and elicit physiological responses like those observed in real-world situations. This allows researchers to study the effects of acute stress on decision making in a controlled and repeatable manner. In [69], a 3D model created using Maya (2020.4) was employed to simulate a suburban environment. Five VR trackers were used to track the body movements of the subjects and synchronize them with a virtual avatar in real time. The subjects wore the VR headset and experienced the virtual environment as if they were avatars. The virtual environment included a simulated arc flash with scenery and auditory representations as well as wind and other effects to increase the subjects' sense of presence. A study [78], created actual industrial shutdown maintenance activities, a VR task. They created a VR platform that included eye tracking and neuroimaging capabilities. Another study [82] measured the conformist judgement, a task involving perceptual decision-making in a virtual group situation. The study revealed two separate conditions that might discriminate between impacts on adjustment. These were likely influenced by social variables and effects that were less precise and likely caused by low-level factors, such as priming. In [67], the authors created a surgical endoscope simulator using Visual Studio C++ (Microsoft, Redmond, WA, USA) and OpenGL (Khronos Group, Beaverton, WA, USA). A single-port surgery robotic endoscope can be maneuvered using the simulator's manipulators, targets, and viewpoints. At these gain settings, the results of the experiment showed a considerable decrease in brain activity connected to stress. This implies that assessing brain activity may be useful in identifying factors pertaining to the operator's emotional state.

11) OUTDOOR TASKS

Some evidence suggests that being outdoors can have a positive effect on decision-making and cognitive function. A health condition monitoring model with four primary stages was used in [84]. First, information was gathered from the environment and biosensors. Second, SVM was used to filter the sensor data and evaluate the indices. Third, using the decision tree method, a risk assessment was performed to forecast mental stress levels. Using the expectation maximization (EM) method, a procedure for selecting wellness-related information was devised. It was found that walking in a natural environment improves the performance in creative problem-solving tasks, compared with walking in an urban environment or sitting quietly indoors. Other research found that nature exposure can improve attention, memory, and the overall cognitive function [99].

12) THE NEWSVENDOR PROBLEM (NP)

The NP is a classic decision-making task first introduced by Edgeworth in 1881 in the field of operations management. It involves a decision-maker who must determine how much of a certain product to order and at what price to sell it. The decision maker faces uncertainty about the demand for the product as well as the cost of holding an unsold inventory [100]. In the NP [101],a news vendor must choose the number of newspapers to buy each day at the wholesale price and then sell them at the retail price. The NP served as inspiration for the experimental technique. In [76] five essential characteristics of the NP were determined: (1) the demand is uncertain, but follows a known distribution; (2) decisions must be made for each time period; (3) there is a cost associated with ordering too many items; (4) the quantity of items ordered in each instance is referred to as the order quantity, which the participants decide for their inventory in each trial; and (5) each trial is independent. The NP model states that the order quantity (q) exceeds the unknown demand (D), and the resulting profit (π) can be determined as a function of q and D using Equation 1 [102].

$$\Pi(q, D) = pmin(q, D) - cq \tag{1}$$

The orbitofrontal cortex (OFC) and frontopolar cortex (FPA) together with the dorsolateral prefrontal cortex (DLPFC) are highly activated by the NP. In addition, the right DLPFC is deactivated, whereas the left DLPFC is activated in more difficult NP circumstances [76].

13) MUSIC TASK

Vocalization, or music, is used as a broad method of expression to convey concepts such as harmony, melody, and rhythm. Its diversity makes it difficult to define, but it can be divided into systemizing and empathizing with music based on understanding and sharing others' feelings, which are frequently expressed through lyrics, music, or video clips [103]. An auditory monitoring task was proposed in [70]. The performance in this exercise was measured by computing the average count of each response. When measuring the reaction time, the gap between the two stimuli was set to five units. Equation 2 shows the determined reaction time, which is defined as the amount of time between the display of a sound and the subject pushing the ''Press me'' button.

$$(100(5 - ReactionTime))/5 \tag{2}$$

Low rhymes were selected for the baby rhythm song and loud rhymes for pop punk tuning. The baby rhythm song belongs to empathizing and is known for its calming qualities, whereas pop-punk is classified as systemizing because of its intense character [104]. Ten sound clips from the International Affective Digitized Sounds system (IADS) that were emotionally evocative (negative valence: 2.147 0.473; high arousal: 7.388 0.494) were presented alongside ten neutral sound clips in [73].

14) VISUAL TASK

Decision making can be particularly affected by tasks that involve visual processing. A stressful situation can lead to changes in cognitive processing, including attention and perception, which can affect an individual's ability to accurately interpret and make decisions based on visual information. Visual monitoring tasks were proposed in [70] and [105]. The experiment used the Computer Vision Lab Walking Pedestrian dataset to provide live video feeds for seven different visual search tasks. These tasks involve a variety of noise stimuli delivered through headphones while being performed in different environments. In [106] four basic emotional states were assessed: happiness, relaxation, boredom, and stress. Information was acquired through random convenience sampling, which involved recruiting 31 participants of various ages. Candy Crush, PubG, and Asphalt Nitro were among the selected games. The findings revealed that the classifiers most accurately recognized happiness, followed by boredom and relaxation/stress.

D. SUBJECTIVE ANALYSIS

Subjective measures of stress involve asking individuals to report their own stress levels and sources of stress in their life. These measures include self-report questionnaires, interviews, and diaries in which individuals write about their stress experiences. Subjective measures are useful, because they allow individuals to report their unique experiences and perceptions of stress. However, they can also be affected by bias and may not always accurately reflect an individual's true stress level [107]. Participants often undergo baseline subjective stress assessments first and then a saliva sample is collected for further examination. A series of visual analog scales that evaluate the subjective perception of stress and the subjective experience evaluation scale are used to assess subjective stress [68]. The Big Five Personality Assessment, which comprises 50 questions, may be administered in conjunction with inquiries concerning the demographic profile of the participants as well as their proficiency in each stress-inducing task [74], [83], [106]. At the end of each stressor task, participants are asked whether they experienced stress during the task [72].which can be realized filling out a form containing certain questions, for instance, an electronic version of the NASA Task Load Index (NASA-TLX) [70], [96]. Cognitive performance can be evaluated using the Mini-Mental State Examination (MMSE) or Cognistat. Cognistat employs either question-and-answer or command-based tasks to measure the cognitive abilities of individuals, and the assessment generally requires approximately 20–30 min to complete [85].

1) PHYSIOLOGICAL MEASUREMENTS

Salivary alpha-amylase is naturally produced and present in the body, specifically in the salivary glands and saliva, and is crucial for the digestion of complex carbohydrates. It is a useful physiological marker of stress and sympathetic nervous system activity, making it a valuable diagnostic tool. The measurement of salivary alpha-amylase levels can provide information on various physiological processes in the body [108]. EEG signals can be captured at various sampling frequencies (e.g., 64 and 250Hz), although 250Hz is more commonly used for clinical and research purposes. According to the international 10/20 system, electrode placements for the 19 channels are categorized as anterior frontal, frontal, central, parietal, temporal, and occipital. Electrode impedance should be kept below 5kΩ for good signal quality. Up to 10kΩ may be acceptable [70], [73], [75], [98]. For fNIRS recordings, different equipment and configurations have been used, including ten transmitter optodes and eight receiver optodes, a dual-wavelength system, a 52-channel probe, and 23 channels in the PFC region. Depending on the study, the sampling rates varied from 8 to 10 Hz, and the system was equipped with different light wavelengths. The detectors of the fNIRS probe were placed on the subject's forehead in accordance with the international 10/20 scheme [73], [74], [76], [77], [80], Figure 4 shows the physiological measurement used by different studies.

E. DATA ANALYSIS

1) PRE-PROCESSING AND FEATURE EXTRACTION

Pre-processing is a crucial step in ensuring the quality of recorded signals and extracting meaningful information. EEG data require several pre-processing steps, including filtering, artifact removal, referencing, and segmentation to remove noise and artifacts and obtain reliable and interpretable signals. By contrast, fNIRS data processing mainly involves the removal of motion artifacts, baseline correction, and signal aging to obtain robust and reliable hemodynamic responses. The sample size for earlier EEG research was

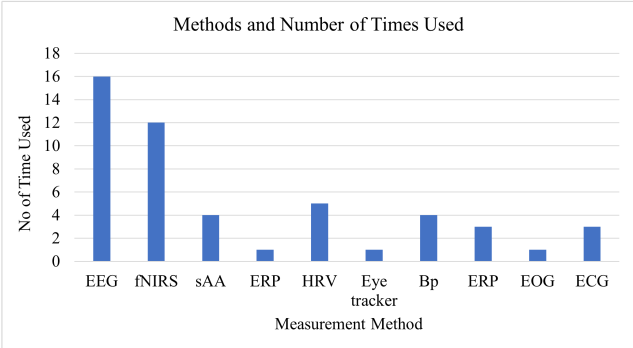

FIGURE 4. Physiological measurement related to recent publication in decision making and stress effects.

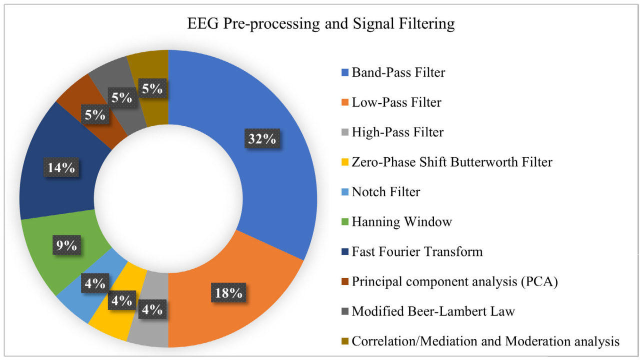

FIGURE 5. EEG Raw data pre-processing and filtering methods.

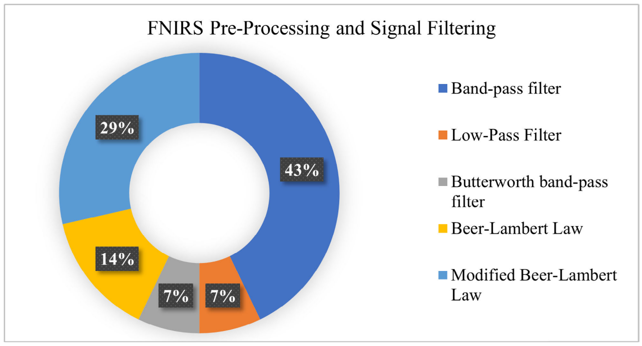

FIGURE 6. FNIRS raw data pre-processing and filtering.

calculated using a power analysis that took into account α-error probability of 0.05 and a power of 0.95 [68], [98], [106]. These studies examined the effects of stress on hemispheric asymmetries and extracted features from the time, frequency, and wavelet domains. Latency-to-amplitude ratios, peak-to-peak signal values, peak-to-peak time windows, peak-to-peak slopes, signal power, mean signal values, kurtosis, mobility, complexity, power spectral densities, band power, entropy, and energy were among the properties included [87]. To facilitate the transition from time domain to frequency domain, they used a short-term Fourier transform with a Hamming window [79], [82], [83], [85], [87]. These studies filtered the electrodermal activity (EDA) through a MATLAB pipeline by downsampling it from 64 to 8 Hz and filtering it with a Butterworth low-pass filter. They applied a fifth-order Butterworth bandpass filter between 2 and 30 Hz to the EEG input. They then calculated the global field power (GFP) for a particular EEG frequency range of interest, which was the beta high range spanning from 21 to 26 Hz. They first identified and rectified blink artifacts. Additionally, a band-pass filtering procedure encompassing 0.1–35 Hz was applied to the EEG signals. The commitment of the stimuli in each trial was synchronized with the segmentation of these signals into epochs. For analysis, they used Welch's power spectral density estimation method to determine the EEG power in the theta band (4–7 Hz) and separately in the alpha band (8–13 Hz). In addition, they calculated the approximate entropy of gaze transitions (ApEn) as a feature to evaluate the participants' overall attentional patterns in the virtual environment. They applied both high-pass and low-pass filters to the continuous data, limiting the frequency range from 0.5 to 30 Hz, in order to analyze event-related potentials (ERPs). Independent component analysis (ICA) and the multiple artefact rejection algorithm (MARA) were applied within the EEGLAB framework to reduce artefacts. Statistical analysis was performed using SPSS 24, and a signal quality index (SQI) assessment was carried out at several stages of the process [81], [84], [96], [109], Figure 5 shows some of the most used pre-processing methods for EEG raw data.

The near-infrared light that penetrates biological tissue allows the use of near-infrared spectroscopy (NIRS), which measures the absorption of light by the neurovascular system to determine the oxygenation status. Bandpass filters are applied to address physiological noise and the modified Beer–Lambert law is used to convert the recorded optical density data into relative concentrations of oxy-Hb and deoxy-Hb [69], [73], [80]. Various methods, including Butterworth filters and polynomial baseline fitting, have been employed to eliminate the high-frequency noise and polynomial baseline fitting [74]. In addition, different mathematical models have been used for further data analysis, such as wavelet transform coherence, graph theory analysis, and general linear models [76]. The fNIRS signals underwent preprocessing using ICA denoising and bandpass filtering. Different filters, including low- and high-pass Butterworth filters, were used to eliminate noise components and artifacts. The cerebral hemodynamic data collected by the fNIRS device were filtered using a bandpass filter, and motion artifacts were corrected using kurtosis wavelet algorithms and spline interpolation. The modified Beer–Lambert law was then used to calculate the changes in oxygenated and deoxygenated hemoglobin levels. Finally, the PMDS was applied to the fNIRS probe to optimize the signal-to-noise ratio during recording [77], [78], Figure 6 shows the pre-processing mechanism used to filter and analyze the fNIRS data.

2) STATISTICAL ANALYSIS

A variety of statistical techniques, including analysis of variance (ANOVA), regression, and correlation tests, including the Mann–Whitney U-test, logistic regression, and Spearman's rho, were used in [65]. These techniques were used to compare groups, examine correlations, forecast results, test cognitive function, and measure brain activity. T-tests and chi-square tests were used to compare demographic data, and statistical analyses were performed using R software, Jamovi software, and MATLAB. Using repeated-measures ANOVA, the effects of stress were evaluated [66]. Using the Homer software (Homer3), a MATLAB-based toolbox, data preprocessing and analysis were performed [69]. Because of the non-normal distribution of the generated data, non-parametric statistical tests were used. The Friedman test was used to compare the continuous measures of SCL and neuromeric activity. Wilcoxon signed-rank tests were used to identify the differences between the high- and low-stress scenarios, whereas Dunn's test was used for post-hoc analysis. For each network-measuring index, a one-way ANOVA was used to evaluate the statistical differences among the four connection states. For multiple comparison analyses, a false discovery rate (FDR) correction was used, employing FDR-corrected $p = 0.05$ at the required level [73]. G*Power 3.1.9 software was used to perform an a priori power analysis to determine the sample size [75]. The Positive and Negative Affect Schedule (PANAS) was used to measure emotional alterations. A mixed three-way ANOVA was used to confirm that the TSST was effective in eliciting acute psychosocial stress reactions [76]. Significant differences between high- and low-margin groups were determined using two-sample t-tests. Using repeated-measures ANOVA testing for HbO2 signals, prefrontal brain activation prior to moral and immoral decisions was examined [80]. Bonferroni-corrected pairwise comparisons demonstrated that conformity is higher in experimental situations than in control situations [82]. The significance level for each two-sided statistical test was set at 0.05. SAS and STATISTICA software's JMP 11 were used for statistical analysis and the values were displayed as mean $\pm$ SE [105]. Each independent variable's unique impact on the dependent variable's prediction was measured. The F-test was used to evaluate the regression model's statistical significance, and the beta coefficient was used to evaluate the individual effects of each predictor [87]. A two-sample t-test was used for each PANAS scale to compare scores between the two groups, with a significance threshold of $p < 0.05$ [76]. A Pearson correlation coefficient was used, with the significance level set at $p < 0.05$, to investigate the relationship between task time and prefrontal brain activation [70]. Using a mixed ANOVA with time (pre- and post-intervention) as the within-subjects component and the intervention group as the between-subjects factor, the effects of the intervention on depression, anxiety, and stress scores were examined. The Bonferroni procedure was used to correct post hoc comparisons for multiple comparisons, and the significance level was set at $p < 0.05$ [74]. Intraclass correlation coefficients (ICC), used to assess measure reliability, showed acceptable reliability for risk-related thoughts, risk perception, risk-taking, and stress. A 5-point scale was used to rate feelings, a 10-point scale was used to rate risk perception, a 5-point scale was used to rate risk taking, and a 10-point scale was used to rate stress. Individuals' risk propensity and trait anxiety were evaluated [88]. Event-related potential (ERP) and time–frequency analyses were used to examine brain activity during a gambling task. They specifically focused on FCz channel data, which is in line with earlier frontocentral electrode research [90]. Repeated-measures ANOVAs were used to analyze the effects of stress, feedback valence, and magnitude on EEG responses, along with Bonferroni-adjusted post-hoc tests for multiple comparisons. ANOVA was used in exploratory analysis to investigate theta-band phase synchrony (ISPS) between the medial and lateral prefrontal locations.

3) CLASSIFICATION TECHNIQUES

In the context of fNIRS analysis, initial data preprocessing is required to clean and extract appropriate information such as changes in hemoglobin concentration. The next step is to carefully select these qualities using statistical approaches to simplify the data and increase their importance. Applying classification methods, such as logistic regression, SVM, random forest (RF), and neural networks, that make use of these features to identify various circumstances or states is the next stage. Insights into the underlying brain activity were obtained by evaluating the model's performance using metrics and interpreting influential features. This continuous procedure guarantees improvements in precision and comprehension. A recent study used logistic regression analysis as a classification method to predict relapse in alcohol use disorder (AUD) patients six months after discharge [65]. Logistic regression analysis revealed that lower oxygenated hemoglobin in the right frontotemporal region and greater gambling thoughts were associated with an increased risk of relapse in patients with AUD. The odds ratio for lower oxygenated hemoglobin in the right frontotemporal region was 0.161, indicating a decreased likelihood of relapse, whereas the odds ratio for greater gambling thoughts was 7.04, indicating an increased likelihood of relapse. These findings suggest that decreased activation in the right frontotemporal region during emotional go/no-go tasks and risk preference in patients with AUD can serve as predictive markers of AUD relapse. In another study, a general linear model (GLM) was employed to analyze fNIRS signals, and its value parameters were adjusted for better performance [69]. By considering the correlations between channels corresponding to the brain, the JCCB-FSC method combines feature selection and classifier modelling into a sparse model. The JCCB-FSC method was developed using intra- and inter-channel regularizers to investigate possible channel correlations and produce distinguishing features [66]. The SVM achieved 88.7% accuracy, RF achieved 91.8% accuracy,

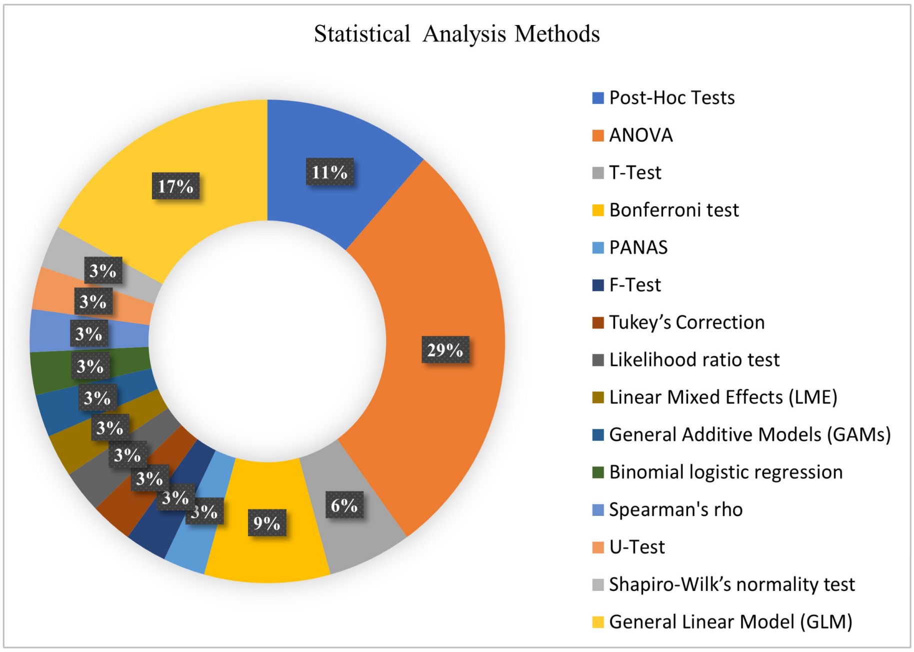

FIGURE 7. Statistical analysis methods used by most of the recent studies.

KNN achieved 87.5% accuracy, linear discriminant analysis (LDA) achieved 87.9% accuracy, and JCCB-FSC achieved a notably high accuracy of 96.1%. The results showed the effectiveness of these algorithms in categorizing the fNIRS data, with JCCB-FSC showing the highest accuracy among the techniques. This study proposed a method based on the CNN approach to assess stress induced by the MIST. The proposed deep learning system has two primary components. A one-dimensional CNN is used in the first section to create instructive activation maps. In the second section, the probability of stress existence is predicted using a stack of completely connected deep layers [77]. The dense neural network (DNN) approach scored 95.11, SVM scored 93.67%, and RF scored 95.61%. Compared with the scores obtained using the CNN method, the CNN approach out-performed all other methods in terms of accuracy, precision, recall, and F1-score, according to the results. The accuracy of the trained model (98.69%) was significantly higher than that of the other models. Another study used supervised machine learning classification models to estimate individual task performance based on fNIRS data in a review session. The models were validated using k-fold cross-validation. The RF classification model achieved the best average classification accuracy of 80.38% in classifying participants' task performance, compared with Decision Tree DT (79.23% accuracy), logical regression (79.61%), KNN (79.23%), and Naïve Bayes (78.5%). [78]. classification models were developed using 12 selected features, including the peak and average Hbo features from different brain regions. The fNIRS data in the review session, along with gaze movement patterns, were significantly correlated with task performance. This study demonstrated that neurophysiological features such as fNIRS data and gaze movement patterns can be used to develop a task performance assessment model under different training scenarios. These findings provide empirical evidence for the use of neurophysiological measures to estimate and predict task performance during industrial training. Fuzzy logic and SVM algorithms enabled the classification of biosensor datasets. The decision tree model and RF algorithm were used to categorize the level of mental stress from health metrics [84]. The mental stress ratio (MSR) was determined based on the evaluation of health indicators, including EEG, BP, HR, and RR. The expectation step (E-step) and the maximized step (M-step) constitute the mental stress ratio EM model.

V. DISCUSSION

These studies have discussed various facets of the complex relationship between stress and decision-making. They revealed that stress can heighten cortical excitability and reduce response caution, leading to faster but less accurate decisions, while also highlighting sex differences in stress responses [86]. Emotional imagery was found to influence risk perception and behavior, with vivid negative risk images moderating the relationship between risk perception and actual behavior [88]. Exogenous cortisol administration increases risk-taking behavior, emphasizing its role in motivated decision-making [87]. Age has been shown to affect risk taking, as older adults exhibit distinct activation patterns in risk-related tasks. The impact of stress on cognitive performance in professional contexts such as nursing varies with lifestyle factors and electroencephalographic variables [73], [86]. Heart rate variability and brain oscillatory activity demonstrated potential sex-related differences in the

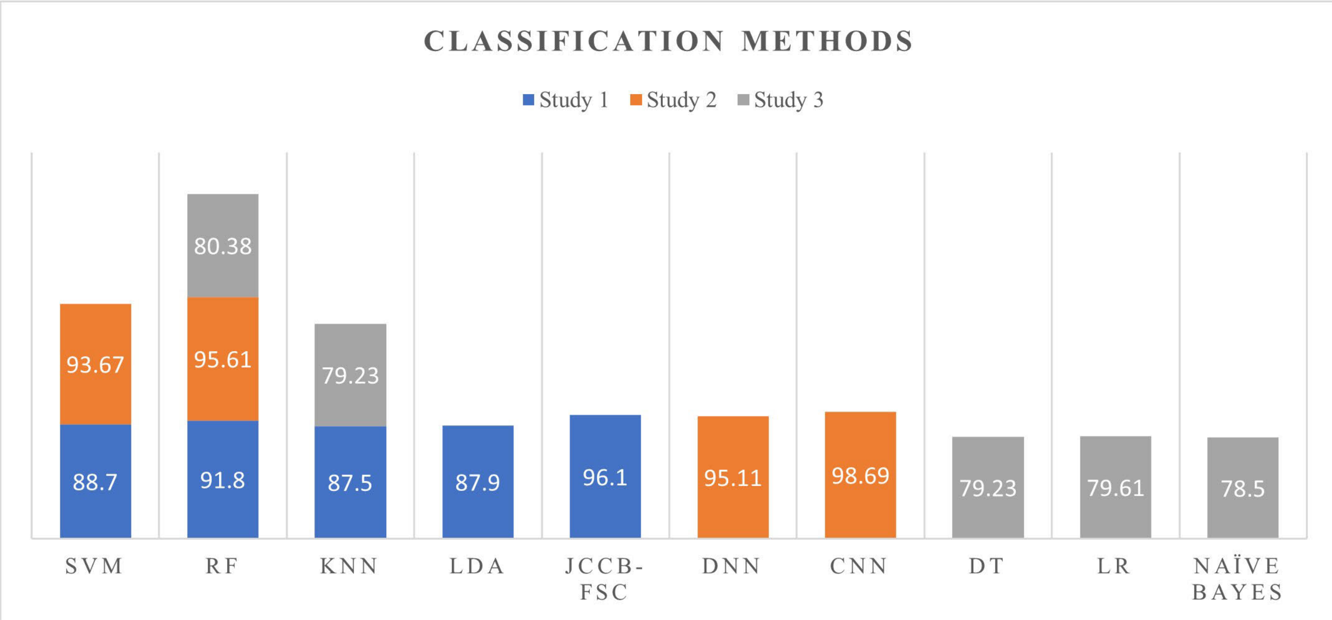

FIGURE 8. **Classification algorithms were used to investigate the effects of acute stress on decision-making.**

response to stress, underscoring the need to consider both physiological and psychological factors [73], [83]. Frontal cortical asymmetry is associated with chronic avoidance orientation and susceptibility to social influence, shedding light on the neural basis of social conformity [82]. Individual differences in moral decision-making have been linked to neural markers, while time constraints have been found to overload the moral brain [80], [81]. Stress has also been shown to impact decision making at various high pressure professions, including firefighting and construction [69], [79]. Innovative neurophysiological measures have been proposed for real-time stress monitoring in occupational settings to enhance safety and performance. These collective findings provide a comprehensive understanding of how stress influences human decision making in diverse contexts [70], [71]. Understanding the impact of stress on decision-making is a crucial area of research with significant implications for various aspects of human life. One prominent aspect explored in these studies is the influence of stress on cognitive processes and decision-making outcomes. Contingent negative variation (CNV) has emerged as a focal point in understanding the role of stress in decision-making. A CNV is a slow cortical potential that occurs when individuals are warned of an upcoming task [89]. Studies have suggested that the CNV reflects heightened cortical excitability and adjustments in response to caution under stressful conditions. This heightened cortical excitability is associated with faster but less accurate decision-making, as individuals prioritize speed over accuracy in stressful situations. Moreover, the influence of stress on decision-making appears to be influenced by gender. While stress was found to impair performance monitoring in both men and women, the effects on feedback processing varied between the sexes [83]. Men showed greater early beta-band power increases in response to stress than women. These findings highlight the need to consider sex-specific responses when studying the impact of stress on decision making and cognitive processes. Emotional imagery and its role in influencing risk perception and behavior are key themes. The intensity of negative risk consequences imagined by individuals is associated with a reduced willingness to take risks. This relationship is mediated by feelings of stress and the perception of risk. Additionally, the presence of vivid negative risk images moderated the connection between risk perception and actual risk-taking behavior [88]. These findings underscore the significant influence of emotional states and mental imagery on decision-making under stressful conditions. The impact of exogenous cortisol administration on decision-making behaviors was also investigated. Cortisol, a stress hormone, was found to increase risk-taking behaviors [87]. This suggests that stress-induced changes in cortisol levels can influence motivated decision making, particularly when risky choices offer potentially significant rewards. However, this shift in risk-taking behavior does not necessarily lead to improved physical performance, highlighting the complexity of the effects of cortisol on behavior [83]. Age-related differences in decision making were also explored. Compared with younger adults, older adults exhibit distinct activation patterns in the PFC during risk-related tasks. These findings suggest that age plays a crucial role in the shaping of risk-related decisions and cognitive processes [86]. HRV and brain oscillatory activity have emerged as potential markers of individual differences in stress responses. Low HRV is associated with stronger theta/alpha desynchronization in women, whereas men with low and high HRV exhibit comparable theta/alpha activity [73]. Additionally, trait anxiety scores influenced power in different brain regions, indicating potentially related differences in responses to stress-provoking situations [83]. Frontal cortical asymmetry has been linked to chronic avoidance orientation and susceptibility to social influence [82]. Individuals displaying stronger right-sided frontal activation during resting-state sessions exhibited chronic avoidance orientation in socially adjusted behavior [65]. This trait is positively associated with susceptibility to social influence, highlighting the intricate interplay between brain activity and social behavior. Individual differences in moral decision-making have been explored, revealing the neural markers associated with variations in moral choices [80]. Alpha event-related spectral perturbations and delta–theta phase-locking coherence play central roles in mediating these differences [81]. Additionally, late alpha activity and delta/theta inter-trial coherence correlate with reaction time and emotional distress perception [69]. Time constraints and their impact on moral competency during decision-making were investigated. These studies highlight how stress can impair cognitive control, increase the risk of misperception, and alter safety behaviors, underscoring the critical importance of stress management and decision-making training in such contexts. Innovative neurophysiological measures have been proposed for real-time stress monitoring in occupational settings, which offer potential solutions to enhance safety and performance [67]. Lightweight EEG and fNIRS were suggested as tools for real-time, out-of-the-lab stress assessment.

VI. LIMITATION AND FUTURE DIRECTION

The study of stress and decision-making can benefit from using neuroimaging methods such as EEG and fNIRS; however, these methods are not without their drawbacks. Owing to their low depth and wavelength sensitivity and consequently poor spatial resolution, fNIRS cannot detect neurovascular changes in an invasive manner. Despite its low spatial accuracy and a propensity for motion artifacts, EEG possesses high temporal precision for measuring electrical activity in the brain. fNIRS combines these advantages and delivers better temporal resolution than fMRI. Researchers must consider these limitations when evaluating the data, particularly in terms of geographical precision. Future research in the fields of cognitive processes, decision making, and stress responses should prioritize several key areas. These include identifying the neural source of CNV, particularly in the pre-supplementary motor area (pre-SMA) and further exploring the neurobiological framework to explain the related phenomena. Understanding the sex-specific effects on feedback processing and stress responses is crucial, necessitating a deep dive into neural mechanisms and considering factors such as personality traits, hormones, and genetics. Integrating methods to measure the impact of affect-laden imagery on risk perception and behavior is essential, combining questionnaires with experimental tasks for validation and ecological validity. Comprehensive longitudinal studies are needed to assess the enduring effects of stress on cognitive performance, especially in high-stress situations such as nursing. Strategies to mitigate the impact of rapid heat stress on cognitive function and decision-making, accounting for user characteristics, and employing larger sample sizes require further exploration. Additionally, future research should focus on the role of stress in group decision-making, emphasizing the dynamic functional connectivity, while improving research methods for enhanced accuracy and reliability in uncovering the complex relationships between stress, decision-making, and cognitive processes.

VII. CONCLUSION

In conclusion, this systematic review has systematically explored the intricate relationship between acute stress and its impact on decision-making researched over the past decade, with a primary focus on physiological measurements. We initiated this review with a comprehensive introduction, providing the context for decision-making and acute stress, followed by an examination of various physiological measurement and objective assessment methods. Stressors and decision-making tasks were thoroughly analyzed. The studies included in this systematic review were rigorously selected, and included articles in English language with strong impact factors. Our attention then shifted towards an in-depth analysis of EEG and fNIRS data, encompassing key aspects such as data preprocessing, feature extraction, feature selection, and the application of machine learning algorithms for classification. In summary, these studies provide a holistic understanding of the multifaceted relationship between stress and decision-making across diverse contexts. These investigations revealed the complex interplay between factors such as cortical excitability, sex differences, emotional imagery, cortisol levels, age-related variations, and individual traits in shaping decision outcomes under stress. Furthermore, the research emphasizes the importance of innovative neurophysiological measures for understanding and managing stress across various domains. As we conclude, it is evident that this systematic review contributes significantly to the comprehension of how stress intricately influences human decision-making. The knowledge gleaned from this review provides valuable insights for researchers and professionals seeking to better understand and address the impact of stress on decision-making processes. Further research in this domain can build upon these findings by focusing on refining experimental designs and advancing our understanding of the dynamic interplay between acute stress and decision-making.

AUTHOR CONTRIBUTIONS

Naufal M. Saad and Frédéric Merienne were instrumental in developing the initial concept and designing the research framework. Abdualrhman Abdalhadi played a key role in formulating the search queries, conducting the literature search, and composing significant portions of the manuscript. Mohd Zuki Yusoff provided support in the review process, whereas Nitin Koundal and Maged S. Al-Quraishi were responsible for editing the manuscript. The remaining sections of the paper received equal contributions from all authors. Furthermore, all authors have thoroughly reviewed and given their consent to the final version of the manuscript.

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