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SURVEY

Exploring Central-Peripheral Nervous System Interaction Through Multimodal Biosignals: A Systematic Review

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ABSTRACT The interaction between the central nervous system (CNS) and peripheral nervous system (PNS) governs various physiological functions, influences cognitive processes and emotional states. It is necessary to unravel the mechanisms governing the interaction between the brain and the body, enhancing our understanding of physical and mental well-being. Neuro-ergonomics-based human-computer interaction can be improved by comprehending the intricate interrelation between the CNS and PNS. Various studies have been explored using diverse methodologies to study CNS-PNS interaction in specific psychophysiological states, such as emotion, stress, or cognitive tasks. However, there is a need for a thorough, extensive, and systematic review covering diverse interaction forms, applications, and assessments. In this work, an attempt has been made to perform a systematic review that examines the interaction between the CNS and PNS across diverse psychophysiological states, focusing on varied physiological signals. For this, scientific repositories, namely Scopus, PubMed, Association for Computing Machinery, and Web of Science, are accessed. In total, 61 articles have been identified within the period of January 2008 to April 2023 for systematic review. The selected research articles are analyzed based on factors, namely subject information, stimulation modality, types of interactions between the brain and other organs, feature extraction techniques, classification methods, and statistical approaches. The evaluation of the existing literature indicates a scarcity of publicly available databases for CNS-PNS interaction and limited application of machine learning and deep learning-based advanced tools. Furthermore, this review underscores the urgent need for enhancements in several key areas including the development of a more refined psycho-physiological model, improved analysis techniques, and better electrode-surface interface technology. Additionally, there is a need for more research involving daily life activities, female-oriented studies, and privacy considerations. This review contributes to standardizing protocols, improves the diagnostic relevance of various instruments, and extracts more reliable biomarkers. The novelty of this study lies in guiding researchers to point out various issues and potential solutions for future research in the field of bio-signal-based CNS-PNS interaction.

INDEX TERMS Central nervous system (CNS), peripheral nervous system (PNS), electroencephalogram (EEG), brain-heart, brain-skin, brain-muscle, differentiation, classification.

I. INTRODUCTION

The perception of human existence consists of thoughts, dreams, and memories. These phenomena are controlled by the interactions that take place between the human brain, body, and the external environment. Such interactions primarily rely on the transmission of information through neural pathways. These pathways connect the brain to various sensors and actuators distributed throughout the human body [1]. The nervous system is remarkably intricate.

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It enables a wide range of cognitive processes and controls various actions. After receiving an immense amount of sensory information from different nerves and organs, Brain processes and integrates this information to generate appropriate bodily responses [2].

The nervous system is a complex network that serves as the control center of the human body. It consists of two main components: the central nervous system (CNS) and the peripheral nervous system (PNS). The CNS, composed of the brain and spinal cord, is responsible for processing and integrating information. Meanwhile, the PNS connects the CNS to the rest of the body, relaying sensory and motor signals. After processing and comprehending the information, CNS transmits specific instructions through the PNS to various parts of the body [3]. The PNS is divided into two major components: the somatic nervous system (SNS) and the autonomic nervous system (ANS). The somatic nervous system is responsible for the voluntary control of body movements. It also helps in the transmission of sensory information from the body to the CNS. On the other hand, the ANS regulates involuntary functions and controls internal processes to maintain homeostasis [2].

The hypothalamus serves as the central core for ANS. It consists of several subnuclei that are responsible for overseeing essential physiological functions, including food digestion and body temperature regulation. Additionally, various peripheral hormones play a role in modulating brain functions. Some of these are Leptin, Insulin, and Gastrointestinal hormones. These chemicals regulate instinctual behaviors such as feeding and also participate in cognitive and emotional activities [4].

The interaction between the brain and PNS is evident when experiencing nervousness or stage fright, leading to sweating and memory lapses. This illustrates how emotional experiences can impact both the PNS through sympathetic innervation of sweat glands and the CNS by impairing memory retrieval [5]. The Brain-Computer Interface (BCI) allows individuals with sensorimotor impairments to interact with computers using their thoughts, enabling communication and control. It benefits those with limited physical abilities but intact cognitive functions [3]. Brain-body interactions can be understood more delicately with a better neural interfacing method. This may offer new treatments for traumatic injuries and diseases that currently lack effective solutions [1]. CNS-PNS interaction also helps in gaining knowledge related to hormonal, and immune responses, challenges, and therapies related to chronic diseases [6].

Neuro-ergonomics explores the relationships between individuals, and the surrounding environment, taking into account individual abilities and limitations. It aims to create work environments that are safe and conducive to a satisfying experience for individuals [7], [8], [9], [10]. Conventional qualitative subjective techniques are insufficient for analyzing the interplay between physical, cognitive, and perceptual aspects involved in daily tasks. It also fails to provide a means to effectively design and evaluate the complicated human cognition and technological systems relationship [9], [11], [12], [13], [14]. Industry 4.0 which is driven by artificial intelligence and automated systems forces humans to interact with continuously evolving technical surroundings. It demands high cognition and perception [15].

Hence, there is a necessity for gaining an understanding of human performance by studying the functioning of the nervous system during everyday life activity [16]. All these things indicate that there should be a rigorous understanding of CNS and PNS interaction. It will help in gathering more knowledge towards integrating humans in this sophisticated age of human-computer interaction (HCI). For this purpose analysis of various bio-signals can be a useful tool. Bio-signals refer to signals that are measured over time from the human body or other organic tissue. It may be electrical, mechanical, thermal, and other types of signals. Physiological signals, such as electroencephalogram (EEG), electromyogram (EMG), electrocardiogram (ECG), and electro-dermal activity (EDA) provide valuable insights into the communication between the CNS and PNS [17].

The CNS signal can be represented by the EEG. It captures the electrical activity of the brain by detecting the potential difference generated in the brain and measuring it on the scalp. There are other types of CNS-originated signals namely magnetoencephalogram (MEG) or electrooculogram (EOG). But from the viewpoint of temporal resolution and cost effectiveness EEG is considered here. The PNS signals can be further divided into the SNS and ANS signals. The SNS signals include EMG, which records muscle activity, and EOG, which measures eye movement. The ANS signals consist of the photoplethysmogram (PPG) and electrocardiogram (ECG), which monitor heart activity and blood flow. Additionally, the Galvanic Skin Response (GSR) measures the electrical conductance of the skin and Electrogastrogram (EGG) measures gastric myoelectric activity. That's why these bio-signals are used to gather valuable information about the interworking of the CNS and PNS [18].

Researchers have put forward several types of stimuli to study mental and cognitive processes. These stimuli include standardized sets of audio-visual materials, film clips, faces, pictures, and words. These stimuli provide researchers with the ability to choose perfect triggers and compare results within controlled laboratory settings [19]. Numerous bio-signals and non-bio-signal characteristics have been utilized to examine human reactions in diverse conditions. However, comprehensive reviews focusing on the interaction between the CNS and PNS using different types of stimuli and the instrumental approaches employed are limited.

This systematic review also points out the comparison of various types of interaction and the psycho-physiological situation of the participants. Additionally, it has the potential to aid in the creation of a standardized protocol for acquiring data and assessing procedures within this domain. This standardized approach will allow for the evaluation of various data collection methods and provide a framework for comparing and analyzing research findings.

The main contributions of this article are summarized below:

1. An encoding scheme is used here to differentiate existing research according to bio-signals used, applications, and analysis aspects of that particular study.

2. This work consolidates various types of interaction between EEG and other physiological signals.

3. Various types of trend analysis in the domain of year-wise publication, data collection procedure, stimuli type, interaction type, psychophysiological states, and analysis technique have been done here.

4. A generalized data acquisition protocol and various instrumental aspects regarding it are discussed in a structured way.

5. Most of the important parameters and features which are used in this type of study are discussed in detail.

6. It also paves the way for future fields of explorations of bio-signal based CNS-PNS interplay across domains such as neuro-ergonomics, healthcare, biomedical, and cognitive psychophysiological research.

The remaining sections of this paper are structured as follows: section II consists of research methodology which includes the involved search strategy, subject information, stimulation modalities, data acquisition protocol, categories to classify papers, comparison of various types of interactions and applications, different types of time domain, frequency domain, time-frequency domain features and statistical parameters used in various studies, classification and statistical analysis used in various studies. Section III discusses the pitfalls of the literature and potential avenues for future research. The final section includes the concluding remarks.

II. REVIEW METHODOLOGY

The methodology for this review is divided into seven subsections to ensure a systematic and organized approach. These include search strategy, subject information, stimulation modality, data acquisition protocol, categories to classify papers, feature/ parameter extraction, and classification/ analysis.

A. SEARCH STRATEGY

This study collected articles from reputable scientific repositories, such as Scopus, PubMed, Web of Science, and the ACM digital library. The articles are gathered within a specific time frame, from January 1, 2008, to April 9, 2023 (6.40 PM). After conducting the preliminary search, a total of 629 articles are identified. Out of these, 127 articles are obtained from Scopus, 82 articles from Web of Science, 109 articles from PubMed, and 311 articles from the ACM digital library.

B. STUDY SELECTION

For conducting this review following keywords are used in Scopus ((eeg OR electroencephalography OR electroencephalogram OR electroencephalographic) AND (synchronization OR brain-body OR interaction OR correlation OR coupling OR (phase-amplitude AND coupling)) AND ((central AND nervous AND system) OR cns) AND (((peripheral AND nervous AND system) OR pns OR autonomic AND nervous AND system OR ans OR autonomic AND activity))).

C. CRITERIA FOR INCLUSION AND EXCLUSION

The PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) guidelines are followed during the selection process to identify articles that are pertinent to the study [20]. Figure 1 displays the PRISMA framework utilized for the literature selection process in this review. Additionally, 121 articles are excluded from the analysis as these are duplicates of already identified articles.

Then exclusion criteria are employed to obtain relevant literature. So, 424 records are removed which discussed animals, diseases, chemicals, prosthetics, non-EEG modalities, databases, demographic studies, pediatric and geriatric cases, historical backgrounds, medicinal remedies, and documentaries. Papers without an interaction between EEG and other physiological signals are also excluded. Some of the papers are also not available on the internet. From the remaining papers, 23 papers which are review papers, editorial papers, or non-English papers are excluded. As a result, 61 papers meet the criteria and are considered for further analysis.

The inclusion criteria of articles are as follows: 1. Papers dealing with the interrelation of EEG with other peripheral signals, 2. Papers related to healthy adult people, and 3.Various types of normal psycho-physiological states namely emotion, cognition, stress, and sleep.

III. RESULTS

A. STUDY CHARACTERISTICS

The year-wise breakdown of the literature is shown in Figure 2 (a). One of the interesting facts that can be derived from these statistics is that the number of papers dealing with the aforementioned interactions is increasing day by day more specifically after 2020. Till 2010 only 3 papers dealt with this topic. But after that, for every 5 years, there are 17, 21, and 20 (N.B. only 1.5 years are considered) no. of papers published on this topic.

Figure 2 (b) shows the modality-wise breakdown of literature. The Pie chart indicates that the Interaction of EEG in these studies is mainly done with Multimodality (41%) and ECG (37.70%). EDA and EMG modalities are used in 11.5% and 6.6% of the total cases respectively. Other types include single modalities namely arterial blood pressure, EOG, PPG, and EGG. There are some special instances also where a particular interaction namely brain-heart, multimodality is used such as ECG and PPG both are considered with EEG.

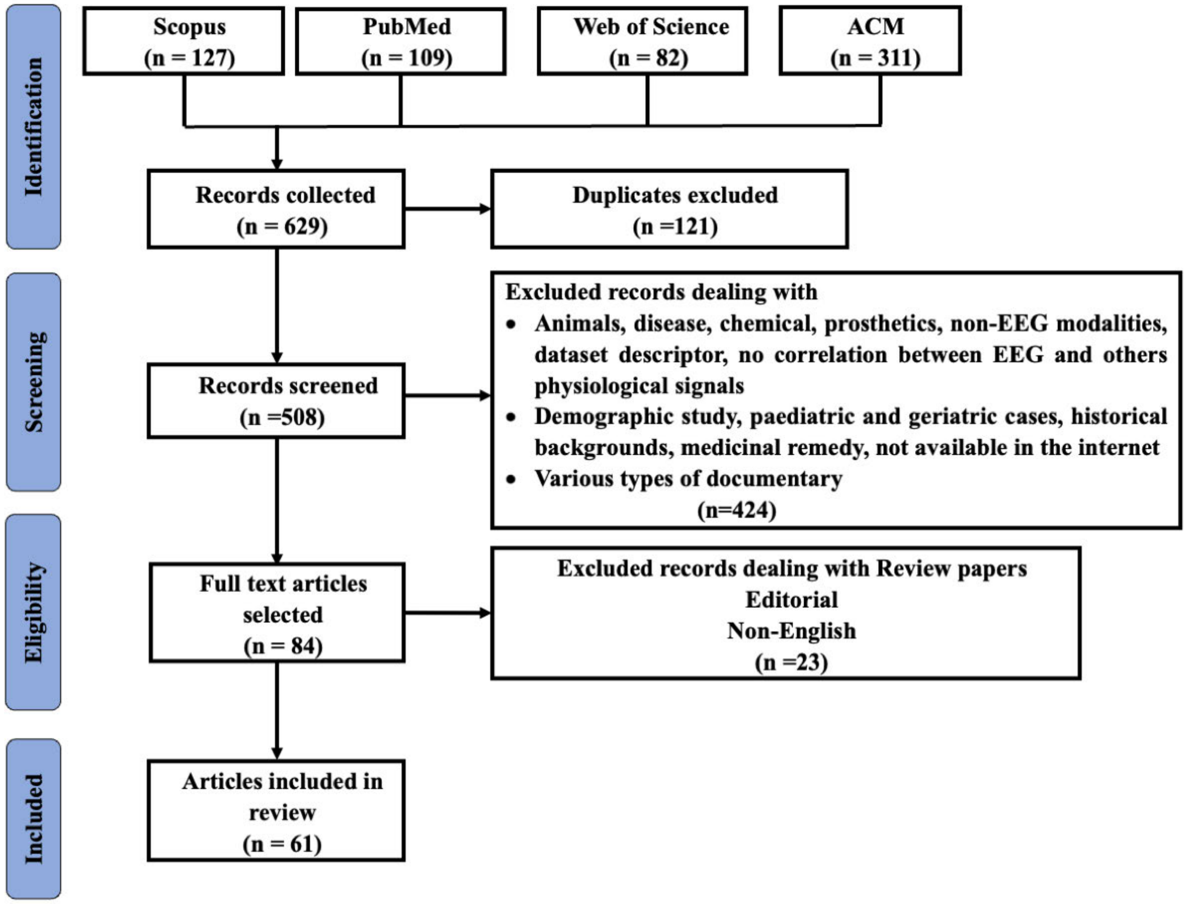


FIGURE 1. The PRISMA flowchart of the article selection process.

B. SUBJECT INFORMATION

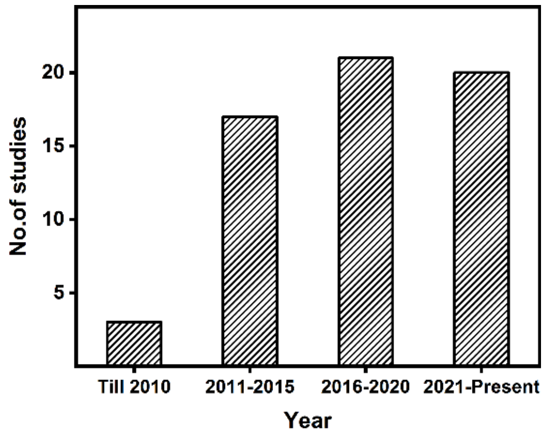
In most of the reviewed papers, 10-50 subjects are considered irrespective of the experiment types. The age of the subjects lies between 16 to 65 years. On average, subjects who are in their 20s or early 30s are mainly preferred for signal acquisitions. Another interesting fact is that around 53 studies are experimental work and only 7 papers have used pre-existing databases. Figure 3 shows the distribution of selected 61 articles based on the data collection procedure.

Subjects in these studies are recruited based on the history of their neurological disorder [21], [22], [23], [24], [25], [26], [27], [28], [29], [30], [31], [32], [33], [34], [35], [36], [37], [38], [39], [40], [41], [42], [43], [44] diabetes [45], [46], obesity [46], cardiovascular disease [25], [27], [30], [34], [42], [45], [46], [47], muscular issues [44], [48], and sleep disorder [49]. People who are taking medications [21], [22], [32], [43], [45], [46], [50], [51], [52], smoking [21], [39], [45], [49], [51], alcohol, tea, coffee [22], [25], [35], [37], [38], [45], [52], [53] are not considered. People who had done strenuous exercise before the experiment are avoided [22], [37], [38], [44], [52].

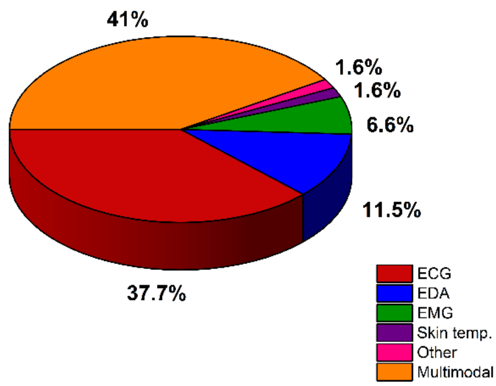
In some papers, subjects are selected by conducting a questionnaire session namely the morningness and eveningness questionnaire [49] and LIPP's questionnaire [51]. Some papers have evaluated their subjects by Annett Handedness Scale [43], mini-mental state evaluation, state-trait anxiety, and Hamilton rating scale [47], Epworth sleepiness scale [49]. In a few of the cases, right-handed people are preferred [18], [21], [22], [25], [39], [40], [41], [44], [45], [50], [51], [53], [54], [55], [56], [57]. Subject's consent is also taken in some literatures [21], [22], [24], [26], [27], [28], [29], [30], [31], [32], [33], [34], [35], [37], [38], [39], [40], [41], [42], [43], [45], [46], [47], [52], [54], [56], [58], [59], [60], [61], and [62]. Meanwhile, there is no information about the consent in other remaining studies.

C. STIMULATION MODALITIES

The quantity and duration of the stimuli vary across different published articles and are not standardized. The experimenter gives different types and amounts of stimuli depending upon the application situation of the experiment. From Figure 4 it is evident that audio stimuli are the most used stimuli in these papers. Though other types of stimuli such as task-based



(a)



(b)

FIGURE 2. **Distribution of selected 61 articles based on (a) year-wise till present (b) based on the signal modalities.**

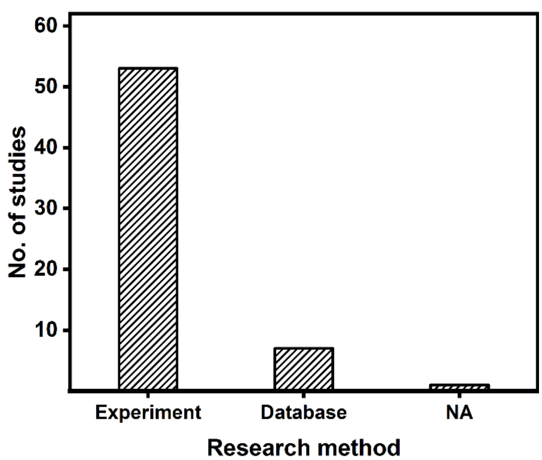


FIGURE 3. **Distribution of selected 61 articles based on data collection procedure.**

stimuli (24.6%), video (16.4%), and audio (6.6%) are also used in a significant number of cases. Some of the studies (21.3%) have not used any stimuli namely in sleep and meditation-based literature. Few of these have not provided any information regarding the used stimuli. Around 7 papers used online public databases for acquiring bio-signals namely DEAP [18], [48], [63], [64], MANHOB-HCI [18], [48], [65], CAP sleep database [66], MERTI-Apps [18], eNTERFACE summer workshop database [50].

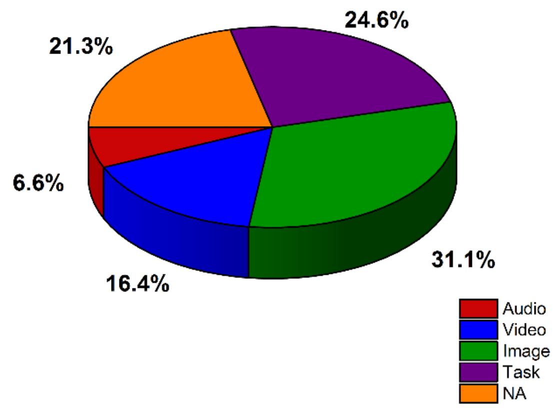


FIGURE 4. **Distribution of selected 61 articles based on types of stimuli.**

Some of the most used stimuli are musical videos [18], [48], [63], [64], [65], visual stimuli [23], [40], [41], [45], [53], [54], [67], images [31], [33], [36], [46], [50], [51], [68], [69], Audio [29], [34], [37], [52], task based stimuli [24], [25], [27], [38], [39], [42], [43], [44], [48], [55], [56], [57], [58], [62], [70], [71], [72], [73], [74], [75], film clips [76], [77], normal video clips [26], [62], [78]. In task-based stimuli either the subjects are instructed to do the mental task (mathematics-related problems, memorizing, computer-based gaming, and reading) or physical task (cold-pressor test, rope skipping, surgical task, and fatigue exercise).

It is seen that audio-visual stimuli dominate other stimuli in eliciting psychological traits. This can be explained with the help of the emotional matrix concept. According to this, any stimuli should be chosen by keeping 5 characteristics in mind, these are Ecological Validity (EV), Temporal Resolution (TR), Controllability (CNT), Complexity (CMP), and Emotional Intensity (EI). As audio-visual stimuli are very close to an actual emotional experience it's EV score is high compared to other stimuli [19].

D. DATA ACQUISITION PROTOCOLS

A generalized protocol is followed in almost all the studies for the acquisition of relevant information from subjects. The flowchart of the protocol is illustrated in Figure 5. The experimenter takes the consent from the subjects before starting the experiment. Subjects are informed about the procedure of the experiment.

Various types of environmental conditions are simulated depending upon the application type of the experiment such as FARADAY's cage [40], [53], CAVE [23], VR environment [24], [76], aCAMS [55], electrically shielded dimly lit room [75]. In the pre-stimulus phase (baseline), the participant is brought back to a neutral situation. It is mostly

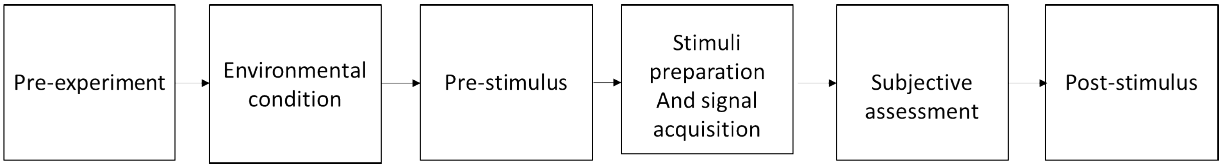


FIGURE 5. Flowchart of generalized data acquisition protocol.

TABLE 1. The experiment protocols used in the database-based articles in recording various modalities using stimuli.

Reference no.	Database	No. of subjects	No of male and female	Device	Sampling rate	Bit quantisation	Psycho-physiological state	Stimuli
[18]	MAHNOB –HCI	30	13,17	ActiveTwo system, Biosemi, Amsterdam, Netherlands	256 Hz	NA	Emotion (Dimensional)	Music videos
	DEAP	32	16,16	ActiveTwo system, Biosemi, Amsterdam, Netherlands	512 Hz		Emotion (Dimensional)	
	MERTI -Apps	62	28,34	MP150 systems, Biopac, Goleta, USA	1 kHz		Emotion (Dimensional)	Videos
[50]	eNTERFACE summer workshop database	5	5, 0	ActiveTwo system, Biosemi, Amsterdam, Netherlands	1024 Hz	NA	Emotion (Discrete)	IAPS images
[63]	DEAP	32	16, 16	ActiveTwo system, Biosemi, Amsterdam, Netherlands	512 Hz	NA	Emotion (Dimensional)	Music Videos
[65]	MAHNOB -HCI	30	13,17	ActiveTwo system, Biosemi, Amsterdam, Netherlands	256 Hz	NA	Emotion (Dimensional)	Music videos
[66]	CAP Sleep Database	108	48, 32	NA	EEG: 100 Hz to 512 Hz	NA	Sleep	NA
[48]	DEAP	32	16, 16	ActiveTwo system, Biosemi, Amsterdam, Netherlands	512 Hz	NA	Emotion (Dimensional)	Music Videos
	MAHNOB –HCI	30	13,17		256 Hz			
[64]	DEAP	32	16, 16	ActiveTwo system, Biosemi, Amsterdam, Netherlands	EEG and EDA : 512 Hz (Before) 128 Hz (After)	NA	Emotion (Dimensional)	Music videos

* Most of the dimensional models include arousal, valence, dominance, familiarity, and liking.
# The discrete model includes calm, positive excitation, and negative excitation.

done through taking rest [22], [23], [24], [25], [26], [45], [62], [71], [79]. Then according to application, the stimulus is applied or task is performed. They are Go/ NoGo task [45], Stroop task [53], Handgrip fatigue task [44], [75], rope skipping [25] and various bio-signals (EEG, ECG, EDA, EMG, PPG, and respiration signal (RSP)) are recorded simultaneously. For sleep, meditation, and resting-based experiments no stimulus is applied [21], [30], [32], [35], [47], [49], [59], [60], [61], [66]. For sleep-related experiments, polysomnography (PSG) is recorded.

Table 1 and Table 2 show the various application types (psycho-physiological state) and stimuli used in every study. Then a subjective assessment is done using various self-evaluation method namely Likert scale [46], [54], Roken Arousal Scale (RAS) [52], Self-Assessment Mannikin (SAM) [18], [23], [48], [63], [64], [78] Karolinska

TABLE 2. The experiment protocols used in the experimental-based articles in recording various modalities using stimuli.

Reference no.	No of subject	No of male and female	Device	Sampling rate	Bit Quantisation	Psycho-physiological state	Stimuli
[21]	45	22, 23	Sagura electroencephalography (EEG)-PSG systems, Sagura Polysomnograph 2000, Sagura Medizintechnik, Mühlheim am Main, Germany	EEG: 256 Hz ECG: 512 Hz	NA	NREM (Non-rapid eye movement) sleep	NA
[22]	18	0, 18	ASA-Lab amplifier, ANT Neuro, Enschede, Netherlands	EEG: 1000 Hz EMG: 2000 Hz	NA	Muscle fatigue , Resting-state	fatigue-exercise
[23]	18	10, 8	TN1132/ST and MLT118F, ADI Instruments, Colorado Springs, USA; Ambu Bluesensor N, Ballerup, Denmark; and Hydrocel Geodesic Sensor Net 64- channel HCGSN, Philips, Electrical Geodesics Inc., Eugene, USA	1000 Hz	NA	Resting state, control (white), color condition (blue)	Visual stimuli
[24]	12	5, 7	Enobio 32-electrode EEG device, Neuroelectrics, Barcelona, Spain; BITalino Revolution device, PLUX Wireless Biosignals S.A., Lisbon; NeXus10 device, Mindmedia, Roermond Herten, Netherlands	PPG, EDA: 512 Hz EEG: 500 Hz EGG: 1000 Hz	NA	Stress	Auditory and visual stimuli (gamming) (can be considered as task)
[25]	32	32, 0	Wired EEG-system, Micromed SD LTM 32 BS, Venice, Italy	EEG, ECG: 1024 Hz 256Hz (after)	NA	Motor Learning	Rope Skipping
[27]	104	64, 50	32-channel cap, Easycap GmbH, Woerthsee-Etterschlag, Germany; BrainVision Analyzer 2.0, BrainProducts, Munich Germany	EEG: 1000 Hz Letter, All signals digitized at 256 Hz.	NA	Sleep, working memory	Math problem
[28]	41	41, 0	G.TEC amplifier, Austria, Electrocap , MV NieuwkoopNetherlands; Velcro strap.	EEG: 512 Hz PPG: NA	NA	Deception	NA
[29]	40	13, 17	V-Amp system, Brain Products GmbH, Gilching, Germany; Biofeedback 2000xpert system, Schuhfried GmbH, Mödling, Austria	EEG: 500 Hz ECG, SCL(skin conductance level), SCR (skin conductance response): 40 Hz	NA	Experimental conditions (Individual vs Social context, Audit vs. Non-audit), Tax-compliance (Voluntary vs. Enforced)	Tax related information (audio stimuli)
[30]	20	10, 10	Compumedics amplifiers and piezoelectric respiratory effort belts, Compumedics, Victoria, Australia; Portapres Model-2, TNO Biomedical Instrumentation, Amsterdam, Netherlands;	EEG: 256 Hz 64 Hz (after) SBP: 64 Hz	NA	Sleep	NA
[31]	22	11, 11	Geodesic EEG Systems 300, Electrical Geodesics, Eugene, USA; MP150 systems, Biopac, Goleta, USA	500 Hz	NA	Emotion (Dimensional)	IAPS images
[32]	21	15, 6	BrainAmp Amplifier, Brain Products, Gilching, Germany; Portapres Model-2, TNO Biomedical Instrumentation, Amsterdam, Netherlands.	EEG,ECG: 500Hz BP : 200 Hz	NA	Resting condition	NA

TABLE 2. *(Continued.)* **The experiment protocols used in the experimental-based articles in recording various modalities using stimuli.**

[33]	150	NA	EEGA-21/26 Encephalan-131-03, Medicom MTD, Taganrog, Russia; Programmable Varicard system, Ramena, Ryazan, Russia	NA	NA	Biocontrol (volition)	Images
[34]	40	21, 19	Compumedics Grael HD-PSG system, Compumedics, Abbotsford, Victoria, Australia	EEG, ECG: 256 Hz	NA	Sleep	Audio
[35]	18	9, 9	Miniature physiological signal recorder, TD1, Taiwan Telemedicine Device Company, Taipei, Taiwan	EEG: 125 Hz ECG: 500 Hz	NA	NREM sleep, REM (Rapid eye movement) sleep, cortical arousal autonomic arousal	NA
[36]	34	8, 26	128-channel Electrical EEG system, Geodesics, Eugene, USA ; V71-23 Isolated Skin Conductance Coupler, Coulbourn, Massachusetts, USA	EEG: 250 Hz	NA	Emotion (Dimensional)	Pictures, Electric pulses
[37]	54	54, 0	32 channel system, Neuroscan, El Paso, USA	500 Hz	16	Volition	Auditory tones
[38]	54	54, 0	32 channel system, Neuroscan, El Paso, USA	500 Hz	16	Volition	Auditory tones
[39]	8	5, 3	Easycap, Herrsching, Germany, SD LTM 64 digital recorder, Micromed, Treviso, Italy; thermistor P-8432,ICBT, Tokyo, Japan	EEG: 1024 Hz (Before) 256 Hz (After)	NA	Vigilance and sustained attention	Mental task with Visual stimuli
[40]	54	26, 28	NeuronSpectrum-4/EP system, Neurosoft, Ivanovo, Russia	2000 Hz	NA	Emotion (Dimensional)	IAPS images
[41]	17	15, 2	Elastic cap, Easycap, Herrsching, Germany, BrainAmp MR plus amplifiers, Brain Products, Gilching, Germany; Monocular SMI iView X camera based system, SMI, Berlin, Germany	500 Hz	16	Error awareness (cognition)	Visual stimuli
[42]	43	43, 0	32 channel system, Neuroscan, El Paso, USA	500 Hz	16	Stress inducing mental task	Mental arithmetic task
[43]	86	12, 74	EEG system, ActiCHamp, Brain Products, Gilching, Germany; Wearable eye- tracker, Pupil Lab GmBH, Germany	EEG: 1000 Hz. Pupilometry:120 Hz (before) 10 Hz (After)	NA	Cognitive load	Working memory task with audio visual stimuli.
[44]	20	NA	16 channel EEG system, actiCAP, Brain Products GmbH, Hofheim, Germany; Spike2 data acquisition system, Science Products GmbH, Hofheim, Germany	EMG: 1000 Hz EEG: 1000 Hz	NA	Muscle fatigue	Handgrip fatigue task
[45]	14	6, 8	NEXUS-32, Mindmedia, Roermond Herten, Netherlands	256 Hz	NA	Go/NoGo task (Cognition)	visual stimuli
[46]	20	9, 11	Marquette Series 8500 7-lead ECG monitor, GE-Marquette Medical Systems Information Technologies, Milwaukee, USA; Lycra EEG stretch cap, Biopac, Goleta, USA,	NA	NA	Emotion (Dimensional)	Recall (Happy, anger), image

TABLE 2. ***(Continued.)*** **The experiment protocols used in the experimental-based articles in recording various modalities using stimuli.**

[47]	42	14, 28	EB-Neuro Be-light©, Firenze, Italy	256 Hz	NA	Resting state with eyes-closed.	NA
[49]	29	13, 16	Astro-Med Grass Heritage Model 15 amplifiers, West Warwick, Rhode island, USA	256 Hz	NA	Sleep	NA
[52]	12	9, 3	EEG1100, Nihon Kohden, Tokyo, Japan	NA	NA	Arousal	Audible random number and massage
[51]	40		Emotiv Epoc Headset device, Emotiv, San Francisco, U.S.A	EEG: 128 Hz	NA	Emotion (Discrete)	IAPS images
[53]	50	26, 24	Neuron-Spectrum-4/EPM device, Neurosoft®, Ivanovo, Russia	2000 Hz 500 Hz (after)	NA	Stroop Task (mental stress)	Visual stimuli
[54]	19	8, 11	MP150 systems, Biopac, Goleta, USA	Skin conductance: 1000 Hz (before) 200 Hz (after). EEG: 500 Hz.	NA	Fear conditioning (Mental stress)	Images, Aversive electrical shock
[55]	7	7, 0	EEG device, Nihon Kohden, Tokyo, Japan	500 Hz	NA	Cognitive load	Control task
[56]	8	7, 1	40 channel NeuroScan system, Neuroscan, Victoria, Australia	EEG and sEMG: 1,024Hz.	NA	Muscle fatigue	Muscle fatigue task
[57]	25	16, 9	wireless EEG recorder, G-Tech GmbH, Austria	EEG: 250 Hz EDA and facial EMG: 1000 Hz (Before) EDA: 50 Hz (After)	NA	Trust (cognition)	AI-based driving game
[58]	43	43, 0	32 channel system, Neuroscan, El Paso, USA	NA	NA	Stress inducing mental task	Mental arithmetic task
[59]	19	0, 19	Computerized sleep-scoring system, Sandman™ Tyco Ltd., Ottawa, Canada	EEG and ECG : 128 Hz.	NA	Sleep	NA
[60]	9	4, 5	Micromed Brain Quick LTM Holter EEG system, Treviso, Italy, Finapres/Portapres system, Finapres Medical Systems, Enschede, Netherlands	512 Hz	NA	Dream	NA
[61]	28	NA	SmartBCI, Mitsar, Russia; PolyRec system, Medical computer system, Russia.	EEG: 250 Hz. Autonomic activity: NA	NA	Meditation	NA
[62]	37	20, 17	9-channel EEG and one lead ECG, BiopacB Alert, Goleta, USA	NA	NA	Mental stress	Video clips (documentary), Stress (digit span task)
[67]	20	11, 9	BrainAmp Amplifier, Brain Products, Gilching, Germany; PSYCHOLAB VD13S system, Satem, Italy.	EEG: 200 Hz Autonomic activity: 100 Hz	NA	Judgement (based on dominance and trustworthiness)	Visual stimuli (images)
[68]	26	13, 13	NA	EEG: 500 Hz	NA	Emotion (Discrete)	IAPS images
[69]	48	32, 16	B-Alert X-10 9-channel EEG device, Advance Brain Monitoring, CA, USA; Shimmer3 GSR+ Unit, Shimmer, Massachusetts, USA; iMotions, iMotions, Inc., Massachusetts, USA	EEG: 256 Hz GSR: 52 Hz	NA	Trust in automation (cognition)	Image –based custom -designed computer -based simulation.
[70]	16	7, 9	128-channel, EGI, Eugene, USA	500 Hz (ECG)	NA	Thermal stress	Cold-pressor test
[71]	30	15, 15	Geodesic EEG Systems 300, Electrical Geodesics Inc., Eugene, USA	NA	NA	Thermal stress	Cold pressor test

TABLE 2. ***(Continued.)*** **The experiment protocols used in the experimental-based articles in recording various modalities using stimuli.**

[72]	44	NA	SC device; Electrocap	EEG: 256 Hz SC (Skin Conductance) and BVP (Blood Volume Pulse):1024 Hz	NA	Emotion (Discrete)	Memorizing digits, and logical exercises.
[73]	25	13, 12	ProComp Infinity, Thought Technology Ltd., Montreal, Canada	Physiological signals: 2,048Hz (before) 256 Hz (After)	NA	Humor detection (cognition)	Reading comic strip
[74]	12	8, 4	Emotiv Epoc Headset device, Emotiv, San Francisco, U.S.A; Shimmer3 GSR+ Unit, ©Shimmer, Dublin, Ireland; DataLITE wireless surface EMG sensors, Biometrics© Ltd, Newport, UK	EEG: 128Hz EDA: 204.8 Hz. EMG: 2 kHz.	NA	Workload prediction (cognition)	Surgical task
[75]	8	3, 5	64 channel eego™sports system, ANT Neuro, Enschede, Netherlands; Trigno™Wireless EMG system, Delsys Inc., Massachusetts, USA	EEG and EMG: 1000 Hz	NA	Functional cortico-muscular coupling, maximum voluntary contraction (MVC) test	Handgrip fatigue task
[76]	25	15, 10	Biopac ECG100C and GSR100C, Goleta, USA; Finapres, Finapres Medical Systems, Enschede, Netherlands; Machines FaceLAB, Eyecomtec, Geneva, Switzerland; Emotiv Epoc Headset device, Emotiv, San Francisco, U.S.A	ECG, GSR and blood pressure: 1000 Hz. Eye gaze and pupil dilation signals: 60 Hz. EEG signals: 128 Hz.	NA	Mental stress	Film clips
[77]	16	7, 9	Nexus X MkII, Mindmedia, Roermond Herten, Netherlands, Enobio. Neuroelectrics, Barcelona, Spain;	ECG and SCL: 512 Hz. EEG: 250 Hz	NA	tagging media (cognition)	Film clips
[26]	12	NA	NA	All signals: 1000 Hz (before) EEG:128 Hz (after) RSP, EDA and PPG: 30 Hz	NA	Emotion (Dimensional)	Video clips (audio-visual stimuli)
[78]	6	4, 2	Biosemi ActiveTwo system, Neurobehavioral systems, Berkeley, USA	EEG: 512 Hz (Before) 256 Hz (After) Other physiological signals: 512 Hz.	NA	Emotion (Dimensional)	video clips
[79]	32	16, 16	ActiveTwo system, Biosemi, Amsterdam, Netherlands	512 Hz	NA	Emotion (Discrete)	Videos
[80]	NA	NA	NA	NA	NA	Emotion (Discrete)	NA

Sleepiness Scale (KSS) [27], Borg Rating of Perceived Exertion scale (RPE) [25]. In a post-stimulus situation, participants are brought back to the neutral state. Both single and multichannel bio-signals are extracted at different sampling rates at a range of 30-2048 Hz. In some cases those signals are down-sampled to reduce processing time [25], [26], [30], [39], [43], [53], [54], [57], [64], [73], [78]. Among database-based emotion-related articles, five papers have used a dimensional model, whereas only one paper has used a discrete model-based database. For experiment-based articles, these numbers stand out as 6 and 5 respectively. The majority of data acquisition devices originate from the USA, Netherlands, Germany, and Italy. EEG acquisition predominantly employs 32-channel systems, although 9, 16, 21, 64, and 128 channel-based systems are also utilized.

E. CATEGORIES TO CLASSIFY PAPERS

In this section, the approach used to determine the categories for classifying the papers will be discussed. Additionally, The discussion will cover how the papers are clustered based on their application, the types of bio-signals studied, and the analysis methods employed.

During the analysis of the literature, various criteria have been identified for segregating papers and approaches, including the utilization of bio-signals to investigate interactions with EEG. Some of the bio-signals used are ECG, EDA, EMG, skin temperature, and multimodal. Some other categories of bio-signals include arterial blood pressure, EOG, PPG, EGG, pupillometry, eye gaze, plethysmograph, wrist motion, salivary cortisol rate, and respiratory signal. The multimodal category indicates the combination of various types of peripheral signals. Some papers have used multichannel instead of single channels for signal acquisition. These papers can be segregated in terms of extracted features or parameters. Out of the analyzed papers, forty-six papers employed linear features, while only six papers utilized nonlinear features. A combination of linear and nonlinear features has been used in ten papers. The 1st condition on which the surveyed literature is encoded is EEG's interaction with particular bio-signals. This is represented as B (Origin, Channels, Features).

The 2nd category utilized to differentiate the different approaches is the domain of application. The concern lies in the interaction of the CNS and PNS. So, the interaction of these bio-signals in various psychological and physical situations is considered. Most prominent among these is the Emotional situation (22 papers). Followed by mental (8) and physical stress (7), cognition (11), sleep (9), volition (3), and vigilance (1). If any study uses less than 10 subjects then it is assumed as a small-size study. Similarly, medium-size (10-50) and large (more than 50) population study is defined. The emotions or whatever the condition felt by participants are quantified using annotations which can be self-reported, expert-based, or the combination of both of these two. In the third case, the matching between the subjective assessment and expert-based assessment is seen [18], [40], [50], [53], [76]. Application (A) type encoding is done as A(Type, Size, Annotations).

Lastly, various types of analysis techniques are used in different literature. Conventional Machine Learning (ML) is used in 13 cases and Deep Learning (DL) is used in 4 cases. While combination both ML and DL is used in 2 cases. In terms of statistical analysis, it is seen that most of the literature employed parametric tests namely ANOVA, t-test, Wald test, Pearson's correlation coefficient, etc. Non-parametric tests namely Friedman's test, Wilcoxon test, Mann-Whitney test, and Spearman's correlation coefficient are also used in various cases. In the overall scenario, statistical methods dominate the analysis techniques which are used in 42 cases among the 61 selected papers. Finally, the last index represents the data collection method i.e. whether the pre-existing publically available online database is used or by experiment data is collected. One interesting fact is that in 53 cases, experimental data is used. Meanwhile, in 7 cases data is directly employed from the databases. Analysis (AN) type encoding is done as AN (Algorithm, Statistics, Assessment).

By merging these 3 coding schemes 61 papers are coded. For example, the paper of Yu et al. [42] is encoded as B(121) A(121) AN(412). It indicates that this paper finds an interaction between EEG and ECG, Multichannel ECG, and linear features are used here. This study is done to assess mental stress with 10-50 no. of participants who have done a self-assessment of the situation. However, ML or DL-based classification is not used here. But for assessing the result parametric statistical methods such as t-test and Pearson's correlation coefficient calculation are used here. The data is collected experimentally. Figure 6. shows the encoding framework used for this literature survey. Table 3 displays the codes assigned to all 61 papers included in this review. It is worth noting that a very small number of duplicates are there, highlighting the research diversity and confirming the effectiveness of the encoding system across different methods.

1) COMPARISON OF VARIOUS TYPES OF INTERACTIONS

After, going through all the 61 literature these studies can be broadly divided into four categories from the perspective of morphological interaction. These are Brain-heart (29), Brain-skin (7), Brain-muscle (4), and Multimodal interaction (21) (here various types of peripheral signals which are generated from different organs are considered). One organ may have different types of related peripheral signals (e.g for the heart there are ECG, PPG, and arterial blood pressure). So to understand each interaction, papers that deal with more than one signal from one organ are also considered [32], [66]. Cases that deal with the interaction of more than one morphologies are considered as Multimodal. When stimuli are applied for assessing various types of interaction, a wide range of physiological signals are obtained through the respective modality acquisition methods. Some of these are EEG, ECG, EDA, EMG, PPG, RSP, and skin temperature.

All of these modalities have some pros and cons. EEG gives information about the neural activity of the brain which is fast and reliable with high time and frequency resolution. However, installation and maintenance are very complex and costly. It has also very low spatial resolution, Signal-to-noise ratio, and very poor estimation of lower cortical neural activity. ECG is portable, non-intrusive, computationally efficient, and has high amplitude compared to other techniques. However, some of its disadvantages are high inter-subject variability and movement artifact-induced low accuracy. PPG is easy to implement on consumer electronics but hand movement results in inaccuracy in tracking PPG signal. EDA signal being one of the real-time correlates is simple, non-obtrusive, easily recordable, and

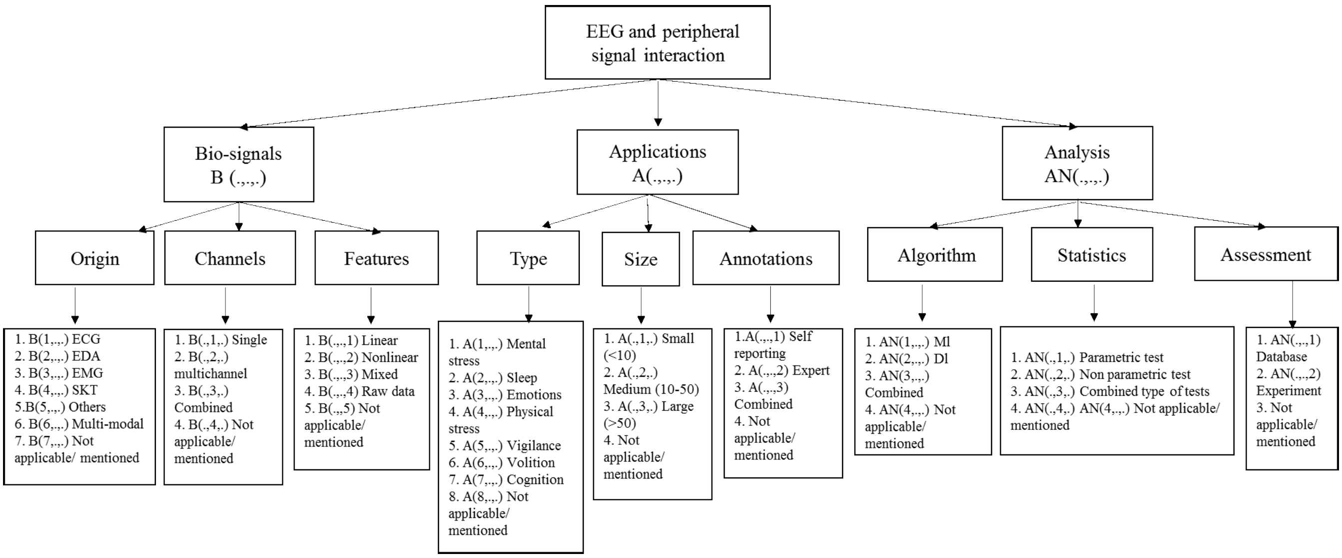


FIGURE 6. Classification of the parameters used for encoding the literature.

TABLE 3. Coding Scheme for all 61 papers.

Code	Reference no.	Code	Reference no.	Code	Reference no.
B(631) A(333) AN(241)	[18]	B(611) A(721) AN(412)	[41]	B(222) A(322) AN(121)	[63]
B(121) A(224) AN(412)	[21]	B(121) A(121) AN(412)	[42]	B(222) A(322) AN(121)	[64]
B(321) A(424) AN(112)	[22]	B(511) A(731) AN(432)	[43]	B(631) A(321) AN(341)	[65]
B(631) A(321) AN(432)	[23]	B(311) A(422) AN(432)	[44]	B(622) A(231) AN(432)	[66]
B(633) A(124) AN(412)	[24]	B(123) A(721) AN(422)	[45]	B(611) A(721) AN(412)	[67]
B(112) A(421) AN(422)	[25]	B(123) A(321) AN(432)	[46]	B(211) A(322) AN(212)	[68]
B(623) A(321) AN(342)	[26]	B(631) A(324) AN(412)	[47]	B(211) A(721) AN(142)	[69]
B(121) A(731) AN(412)	[27]	B(111) A(224) AN(412)	[49]	B(121) A(424) AN(422)	[70]
B(621) A(721) AN(142)	[28]	B(611) A(313) AN(142)	[50]	B(111) A(424) AN(422)	[71]
B(611) A(721) AN(412)	[29]	B(611) A(122) AN(432)	[51]	B(211) A(321) AN(142)	[72]
B(611) A(224) AN(412)	[30]	B(121) A(321) AN(412)	[52]	B(611) A(711) AN(132)	[73]
B(621) A(322) AN(422)	[31]	B(111) A(123) AN(412)	[53]	B(631) A(721) AN(132)	[74]
B(621) A(324) AN(422)	[32]	B(211) A(121) AN(431)	[54]	B(312) A(414) AN(412)	[75]
B(111) A(634) AN(422)	[33]	B(111) A(714) AN(112)	[55]	B(613) A(123) AN(312)	[76]
B(111) A(224) AN(432)	[34]	B(321) A(414) AN(432)	[56]	B(621) A(721) AN(112)	[77]
B(621) A(214) AN(412)	[35]	B(631) A(721) AN(312)	[57]	B(633) A(313) AN(122)	[78]
B(211) A(321) AN(412)	[36]	B(123) A(121) AN(412)	[58]	B(123) A(321) AN(422)	[79]
B(123) A(634) AN(412)	[37]	B(122) A(224) AN(412)	[59]	B(121) A(321) AN(421)	[48]
B(123) A(634) AN(412)	[38]	B(121) A(214) AN(432)	[60]	B(141) A(344) AN(442)	[80]
B(411) A(511) AN(412)	[39]	B(611) A(324) AN(412)	[61]		
B(611) A(333) AN(412)	[40]	B(111) A(121) AN(122)	[62]		

low-cost. But it is also easily influenced by temperature and humidity. Although EMG has good spatial resolution it is contaminated by noise and time resolution is poor. Again, RSP has a problem with motion artifact it is useful for non-contact and long-term monitoring [19].

Due to this kind of incongruous nature of each physiological signal various combinations of earlier mentioned modalities have been tried out for understanding the interaction of CNS and PNS. These signals can be acquired as multichannel or single channel. Typically, multi-channel ECG signals are characterized by their complexity and large data size. The presence of multiple leads also enables the direct application of Convolutional Neural Network (CNN) and Recurrent Neural Network (RNN) architectures. Most of the papers used multichannel signals compared to a single channel. For classification or analysis, features are extracted from the signals. linear features are preferred over nonlinear features in most of the literature. Figure 7 demonstrates the distribution of selected 61 articles based on the types of interaction used by the researchers.

2) COMPARISON OF VARIOUS TYPES OF APPLICATIONS

Neuroergonomics is an interdisciplinary field that integrates neuroscience and ergonomics to investigate human performance under various daily life circumstances by analyzing different types of recorded physiological signals [16]. In some of the emotion-related studies elicitation is done by showing musical videos [18], [48], [50], [63], [64], [65],

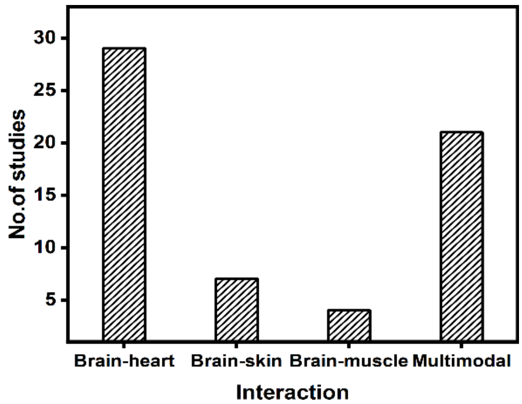


FIGURE 7. Distribution of selected 61 articles based on types of interaction used by the researchers.

happiness recall task [46], video clips [26], [78], [79], film clips [76], and IAPS Images [31], [40], [46], [51], [68].

Mental stress is imposed by arithmetic task [27], [38], [42], [58], Stroop task [53], control task [55], video clips [62], images [51], [54], gamming [24], and film clips [76]. Physical stress is induced by cold pressor task [70], [71], rope skipping [25], fatiguing exercise [22], [56], handgrip task [44], [75]. Cognition is evaluated using go/no go task [45], surgical task [74], audio stimuli [29], images [67], [69], visual stimuli [41], film clips [77], reading comic strips [73], audio visual stimuli [43], gamming [57], and deceptive task [28]. Sleep based task is also done in some cases namely [21], [27], [30], [34], [35], [49], [59], [60], [66]. Volition-related papers used biocontrol by showing images [33], and auditory tones [37], [38]. Vigilance is also studied using a mental task [39].

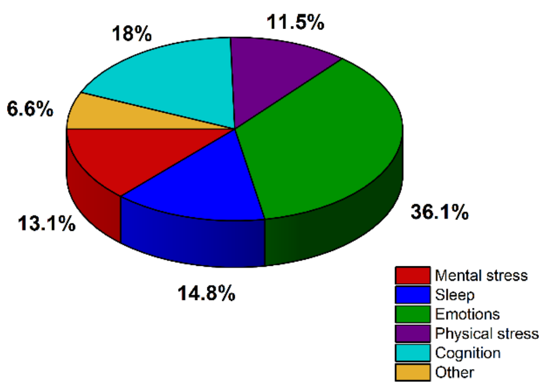


FIGURE 8. Distribution of selected 61 articles based on types of applications used by the researchers.

Most of the paper (44) deals with 10-50 participants. Small no. of participants (<10) are there in [35], [39], [50], [51], [55], [56], [60], [73], [75], and [78]. Large no. of participants (>50) are there in [18], [27], [33], [37], [38], [40], [43], and [66]. Figure 8 shows the share of various applications among the selected papers. As volition and vigilance are contributing less compared to other applications these are clubbed together in other category. The process of annotating or labeling physiological signals requires specialized expertise and can be both costly and time-consuming. In this survey, 3 types of annotation have been seen. In most of the case, self-annotation is done. Expert based annotation is also done in some literatures [31], [44], [51], [63], [68], and [64]. Mixed annotation can be done for more clarity [18], [40], [50], [53], [76], [78].

F. FEATURE / PARAMETER EXTRACTION

For classification and analysis, various types of features have been extracted. Some of these are time domain, frequency domain, and time-frequency domain features.

1) TIME DOMAIN FEATURES EXTRACTION

For EEG, the following time domain features are extracted namely N550 latency and amplitude [34], mean [18], [50], [57], [69], maximum [18], minimum [18], standard deviation [50], [57], [76], skewness [50], [76], kurtosis [50], [76], variance [57], [69], peak-to-peak amplitude [57], [69], mean of the absolute values of the first difference of raw signals [18], [50], and mean of the absolute values of the first difference of normalized EEG signal [50]. Some of them also have used power spectra of one second EEG epoch [55], approximate entropy [46], corrected conditional entropy (CCE) [38], duration of overall NREM [21], number of Slow oscillation events [21], global power [36], the correlation coefficient between two channels [69], root mean square value and energy of EEG signal [69], median frequency (MF) and mean power frequency (MPF) of resting state EEG.

For ECG, the following features are extracted namely heart rate [29], [32], [42], [55], [67], inter-beat interval [32], [73], maximum successive systolic blood pressure amplitude values in relation to the previous R-peak [73], mean RR interval [31], [52], [77], [78], standard deviation of RR interval (SDNN) [23], [40], [46], [53], [74], [77], [78], root mean square of the successive differences (RMSSD) [23], [40], [53], [74], proportion of adjacent pulse to pulse intervals that vary by more than 50 milliseconds (pNN50) [53]. Some of the papers have also used the following features such as heart rate deceleration [41], standard deviations of Poincare plot in terms of short-term variability (SD1) and long-term variability (SD2) [79], the magnitude of the peak in cardiac acceleration and deceleration, differences in baseline pretone cardiac activity [34].

For EDA, the following features are extracted namely mean [18], [40], [50], [74], mean of derivative [18], [50], the standard deviation of EDA signal [50], [74], skin conductance response (SCR), skin conductance level (SCL) [40], [67], range of SCR [23], the slope of SCL [24], peak rate of SCR [24], mean of SCL [57], [77], number of SCRs [73], mean SCR [73], and maximum SCR amplitude [57], [68], [69], [73]. Some of the least used features are latency to the maximum SCR [73], the relative latency [73], latency to the first SCR [57], [68], [73], the relative latency [73], no. of peaks [74], the sum of the SCR-amplitudes of the significant SCRs [57], [69], average phasic driver [57], area of phasic driver [57], trough-to-peak response latency of first significant SCR [57], mean skin conductance (SC) value (global mean) [57], z-scored SCR [54], SC changes [36], rise time [68], and SCR duration [68].

EOG-based features are eye blinking rate [18], mean and variance of EOG signal [18]. From PPG following features are extracted: Range of pulse to pulse intervals (dRR) [61], mean of pulse to pulse interval (RRNN) [61], SDNN [61], coefficient of variation [61], median [61], amplitude of median [61], RMSSD [61], volumetric changes in blood in peripheral circulation [18], mean heart rate [18], standard deviation of heart rate [18], variance of heart rate [18]. Following EMG features namely the mean and peak-to-peak amplitude of facial EMG [57], the energy of special muscle (Zygomaticus, Corrugator) signal [18] are also explored in some literature.

Some of the other types of features are mean blood pressure [50], Distal-to-proximal skin temperature gradient [39], mean, standard deviation, minimum, maximum of skin temperature [50], pupil diameter [41], [43], The mean and standard deviation of three-axis gyroscope, accelerometer [74]. From respiratory signal following features are extracted: fundamental respiratory frequency over time [31], mean [50], mean of derivative [50], standard deviation [50], range [23], [50], respiratory rate [61], respiratory amplitude [61].

2) FREQUENCY DOMAIN FEATURES EXTRACTION

For EEG, the following frequency domain features are extracted namely lateralization index [18], [46], [51], [77], [78], delta power [21], [23], [24], [27], [29], [39], [47], [57], [62], [65], [67], [68], [26], [70], [76], [79], theta power [23], [24], [26], [29], [31], [39], [40], [43], [45], [47], [53], [54], [57], [62], [65], [67], [70], [76], [79], alpha power [23], [24], [26], [29], [31], [33], [35], [40], [43], [44], [45], [46], [52], [53], [54], [57], [62], [65], [67], [70], [73], [76], [79], beta power [23], [24], [26], [29], [31], [35], [39], [40], [44], [53], [57], [62], [65], [70], [73], [76], [79], alpha 1 power [47], alpha 2 power [47], beta 1 power [33], [39], [47], beta 2 power [39], [47], gamma power [23], [24], [26], [29], [31], [40], [44], [47], [53], [57], [62], [65], [67], [79], beta/alpha ratio [77], Beta / (Alpha + Theta) ratio [72], EEG power spectrum (12–15 Hz) [27], alpha/theta ratio [45], [61], Beta power/ (Alpha power + Beta power) [73], gamma 1 power [73], gamma 2 power [73], alpha/beta ratio [61], HF/LF ratio [60], where high frequency (HF) is the PSD in the frequency range of [20–50] Hz, and low frequency (LF) is the PSD in the delta band, sigma power [21].

Other types of EEG based features include mean power from the EEG (in relation to each RR-interval), mean, variance, and energy of various decomposed bands [32], [69], fast-wave mean amplitude (FWMA) [59], amplitude-weighted frequency (AWF) [59], occurrence probability of delta wave (OPDW) [59], power spectra of one second EEG epoch [55], ratio of absolute delta power over total power [30], total EEG power [27], mean, maximum, integral of Power spectrum density (PSD) from slow alpha [18], alpha [18], beta [18], Gamma [18], Hjorth parameters (Activity, Mobility and Complexity) and fractal dimensions [26], [76], P300 and P100 evoked potential [68].

For ECG, the following features are extracted namely HF power [21], [31], [35], [37], [38], [42], [46], [47], [48], [58], [60], [67], [73], [74], [76], LF power [21], [35], [37], [38], [42], [46], [47], [48], [54], [58], [60], [73], [74], [76], LF/HF ratio [35], [37], [42], [46], [47], [48], [53], [58], [60], very low frequency (VLF) power [73], [74], total power [21], [33], [38], [42], Systolic and diastolic arterial pressure, LF/HF [60], HF peak frequency [21], complexity index and logarithm of HF and LF spectrum [45], and inter-beat interval peak frequency [73].

From EOG only one type of frequency domain feature is used i.e. LF power [35]. From PPG HF, LF, logarithmic HF, and logarithmic LF are extracted [24]. From EGG normalized signal power for bradygastria, normogastria, and tachygastria is extracted [24]. In one study, the respiratory signal power in 10 frequency bands between 0.25 Hz to 2.75 Hz are also used [50]. From EMG median frequency [22], [44], and mean power frequency [22] is extracted.

3) TIME-FREQUENCY DOMAIN FEATURES EXTRACTION

From EEG, the following time-frequency domain features are extracted namely wavelet packet energy [46], absolute value of logarithm, and power of discrete wavelet transform (DWT) from slow alpha, alpha, beta, and gamma band [18], average wavelet energy in the beta and gamma bands [56], Relative Wavelet Entropy [78]. From EMG cumulated and average wavelet energy in sEMG during pre- and post-muscle fatigue is extracted [56].

4) STATISTICAL PARAMETER EXTRACTION

Some of the important parameter extracted for statistical analysis are brain heart interplay coupling coefficient [48], [70], [71], directed transfer function [28], [37], [58], partially directed coherence [28], [67], modulation index [21], [24], [39], [63], slow oscillations – heart rate intervals [49], multiscale fuzzy measure entropy [25], Wiener–Granger causality interactions [66], system in error range (SIE), time percentage for system in transition zone (SIT), absolute system error (ASE) [55], coherence index [22], clustering coefficient [22], local efficiency [22], global efficiency [22], characteristic path length [22], time-delayed maximal information coefficient [56], transfer spectral entropy [75], Granger causality [75], cortico-muscular coherence [44], cortico-cortical coherence [44], stress index [33], [61], cardiac vagal index [79], sympathetic index [62], [79], sympathovagal balance index [79], parasympathetic index [62], phase-amplitude coupling (PAC) profile [24].

G. CLASSIFICATION AND STATISTICAL ANALYSIS

In order to classify and distinguish between various psycho-physiological states, a variety of statistical analysis and classification methods are employed. In this context, features are extracted from diverse signals. The conventional ML technique has been used in 13 cases, with 4 papers dealing with the DL technique, meanwhile, 2 papers have used both ML and DL. Statistical analysis is done in 42 studies. Figure 9 illustrates the distribution of 61 selected papers, categorizing them based on the analysis techniques employed by researchers.

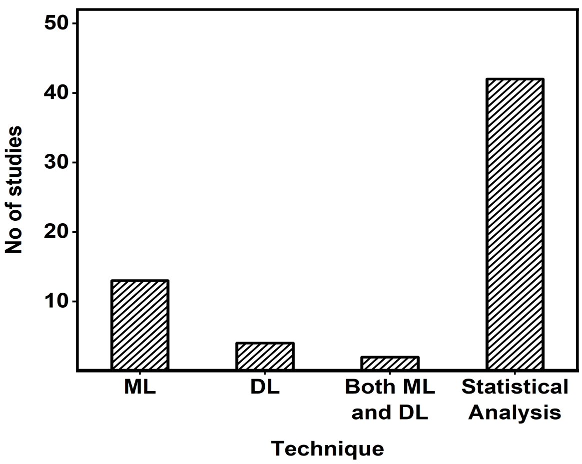


FIGURE 9. Distribution of selected papers 61 articles based on types of analysis techniques used by the researchers.

1) CLASSIFICATION

Table 4 provides a gist of the classifiers used in the study, along with their corresponding performance metrics such as accuracy, F-score, and target classes. Among the 19 literatures which are performing classification, 8 of these are employing emotion-related classification [18], [26], [50], [63], [64], [65], [72], [78]. Some of the popular target classes are positive/negative/neutral valence, low/high/neutral arousal, low/high liking, calm, joy, fear, happiness, and melancholy. Another type of popular psycho-physiological state for classification is cognition. Where various studies have classified between truth and lie [28], low, high, normal and very high cognitive task load level [55], [74], funny, not funny [73], low or high trust [57], [69], and High /low interest [77]. Stress related classification is done to know about stress level [22], [62], [72], [76].

The best classification can be seen in the paper of Sharma et al. where a multimodal approach using EEG, ECG, EDA, arterial blood pressure, and eye gaze data from 25 subjects is employed. Around 1334 features are extracted from these signals and then the Genetic algorithm is used for the feature selection. The student's t-test showed the relevance of the Genetic algorithm. Selected features are applied to support vector machine (SVM) and artificial neural network (ANN). Among them, ANN gives the best result in classifying stress and non-stress situations with average accuracy and F- score of 95% and 94% respectively [76]. Song et al. paper performs least in detecting levels of arousal and valence with an accuracy of 61.5% and 58% respectively. However, DL models such as 1D-CNN, 2D-CNN, and MLP with multimodal approaches are used here.

Most of the classification-related works employed multi-modal approach [18], [26], [28], [50], [57], [65], [73], [74], [76], [77], [78]. Meanwhile, significant no. of EEG and EDA-based classification is also visible in [63], [64], [68], [69]. There is a huge no of brain-heart interactions using EEG and ECG interactions. But among these only 2 articles have done classification with an accuracy of 76.67% and 77% for cognition and stress levels respectively [55], [62]. Some of the widely used classifier is SVM [55], [74], [77], [78], LDA [28], QDA [50], [57], [69], k means clustering [63], [64], naive Bayes [62], random forest [73], various types of neural network namely ANN [68], [76], long short term memory (LSTM) [18].

Liang et al. have used a combination of various classifiers namely SVM and backpropagation (BP) neural networks to categorize positive, negative, and neutral emotions which give 90.66% average accuracy. Ajenaghughrure et al. used an ensemble classifier which is a combination of QDA, SVM, MLP, and GNB for classifying low and high trust with an accuracy of 68.10% and f-score of 76.60%. Some of the feature selection algorithms are PCA [28], Laplacian Eigen map [55], Minimum redundancy maximum relevance score [62], genetic algorithm [50], [76], ant colony optimization [18], ReliefF, Sequential forward floating selection [43], t-test-based feature selection, ICA [74], Pearson correlation coefficient, Wilcoxon rank-sum test [57], [73], ANOVA test [68]. Li et al. have achieved an r-value of 0.691 for the prediction of individual fatigue tolerance using the SVR model. This model is based on the network properties of the resting-state EEG in the beta band of 18 subjects before exercise [22].

Out of 7 articles which has used pre-existing databases, 5 of these have done classification [18], [50], [63], [64], [65]. Among these Hwang et al. [18] and Rivera et al [48] even used 3 (MAHNOB-HCI, DEAP, MERTI-Apps) and 2 (MAHNOB-HCI, DEAP) databases respectively to validate their classifiers [18].

2) STATISTICAL ANALYSIS

Statistical analysis has been carried out in 42 selected studies. Most of the analyses are divided into 3 categories such as: 1) Parametric test where it makes assumptions about the underlying distribution of data, such as normality, 2) Non-parametric test where such type of assumptions are not taken into consideration, 3) combination of both parametric and non-parametric tests. Around 28 papers used parametric tests and 13 papers used nonparametric tests. A combination of these two approaches is applied in 12 papers.

Some of the parametric tests used in various literatures are ANOVA [21], [23], [27], [29], [30], [34], [35], [36], [40], [41], [43], [44], [46], [54], [56], [57], [66], [67], [68], [74], [75], [77], T-test [21], [27], [34], [35], [36], [37], [38], [39], [40], [42], [43], [46], [51], [53], [56], [58], [67], [74],

TABLE 4. The summary of classifiers and respective performance metrics.

Reference no.	Feature selection algorithm	Classifier	Target classes	Classification performance	
				Average accuracy (%)	F-score (%)
[18]	Ant Colony Optimization (ACO)	Bidirectional LSTM	Arousal, Valence	Arousal: 78 Valence: 81	-
[22]	-	Support vector regression (SVR)	Muscle fatigue tolerance prediction	0.691 (r value)	-
[26]	-	SVM, Back Propagation (BP) Neural Network	Positive, Neutral Negative emotion	90.66	-
[28]	Principal Component Analysis (PCA)	linear discriminant analysis (LDA)	Truth, Lie	84.14	86.31
[50]	Genetic algorithm (GA)	Quadratic Discriminant Analysis (QDA)	Positively excited, negatively excited, and calm	76.66	-
[55]	Laplacian Eigen map	Support vector machine (SVM)	low, normal, high, and very-high cognitive task load level	76.67	-
[57]	Sequential forward floating-point wrapper feature selection method.	Ensemble classifier (combination of QDA, SVM, MLP, Gaussian Naive Bayes(GNB)	Low trust, high trust	68.10	76.60
[62]	Minimum redundancy maximum relevance (MRMR) scores.	Naïve Bayes classifier with a Gaussian kernel	Low, high stress level	77	-
[63], [64]	-	K means clustering	high arousal, low arousal, neutral arousal, high valence, low valence, and neutral valence	-	-
[65]	-	2D CNN, MLP	Arousal, Valence	61.5, 58	-
[68]	Analysis of variance (ANOVA)	Neural network classifier	Joy, Fear, Happiness, Melancholy	80,100, 80,70	-
[69]	ReliefF, Sequential Forward Floating Selection	QDA	Trust, Distrust	78.55	-
[72]	-	Dynamic Bayesian network	Positive and negative emotion.	82%	-
			Stress, confusion, frustration, boredom	81%-90%	
[73]	Pearson correlation coefficient, Wilcoxon rank-sum test	Random Forest (RF)	Funny, Not funny	88 (AUC)	-
[74]	t-test-based feature selection and Independent component analysis (ICA)	SVM	Cognitive workload levels	83.20	81.1
[76]	Genetic algorithm	Artificial Neural Network (ANN)	Stress, no stress	95	94
[77]	-	Support Vector Machine (SVM)	High /low interest	Approx. 85	Approx. 90
[78]	-	SVM	Positive/negative valence, low/high arousal, and low/high liking	69.58%, 73.66%, and 70.25%	-

[76], Watson– Williams's multi- sample test [21], [47], [60], Wald test [39], Mauchly's test [67], Pearson's correlation coefficient [22], [24], [27], [29], [35], [40], [42], [47], [49], [52], [53], [55], [58], [59], [61], [73], [74], [77].

Some of the non-parametric tests are Friedman's test [44], [48], [62], [70], cluster based permutation test [25], [43], [48], [56], [70], [79], Wilcoxon test [24], [31], [32], [33], [44], [45], [48], [51], [62], [66], [70], [71], [73], Mann-Whitney test [33], [45], [60], Chi-square test [31], [33], [74], Kruskal-Walli's test [33], Shapiro-wilk test [23], [34], [45], [51], [54], Kolmogorov–Smirnov test [25], [51], [66], Bootstrap hypothesis testing [63], [64], Spearman's correlation coefficient [25], [45], [46], [48], [60], [63], [78].

For measuring effect size cohen's kappa [74], [78], or cohen's d [24], [63] is also used [24], [63], [74], [78]. In order to address the issue of multiple comparisons, some correction strategy is also employed to mitigate its effects such as Greenhouse– Geisser correction [21], [23], [29], [40], [41], [43], [47], [54], [57], [60], [67], [69], [75], false discovery rate (FDR) correction [21], [23], [53], [61], [67], Bonferroni correction [27], [29], [31], [44], [57], [63], [64], [67], [73], Bonferroni–Holm procedure [41], Huynh-Fedlt correction [57].

IV. DISCUSSION

The study emphasis on the systematic integration of various physiological signal interactions of CNS and PNS through the consolidation of a broad range of psychophysiological states. Post-2020 trend analysis reveals a significant surge of CNS-PNS interaction studies, highlighting the necessity for such investigations. The systematic review places particular emphasis on crucial metrics in this domain, such as EEG band power and heart rate variability. By critically evaluating past research, the study unveils variations in experimental frameworks and emphasizes the necessity for standardization and generalized datasets. It also suggests future exploration avenues of CNS-PNS interaction using various physiological signals.

The measurement of the interaction of the CNS and PNS using physiological traits is generally straightforward. However, the specific requirements for measurement can vary greatly based on experimental factors such as its type, applications, and analysis being used. Most of the papers that have used publically available databases mainly focus on various emotional state classifications only. So it indicates there is a lack of publically available databases for the study of CNS- PNS interaction in various situations such as stress, and cognition.

There is an abundance of emotion recognition-related work. In numerous articles, emotion models have been categorized into two main groups based on their theoretical frameworks: (a) discrete and (b) dimensional models. Discrete emotion theories propose universal fundamental emotions rooted in identifying six core emotions: fear, disgust, surprise, anger, sadness, and happiness [81], [82]. However, annotators may struggle to distinguish closely related emotions in this model. Dimensional emotion modeling suggests interconnected emotions using arousal, valence, and dominance dimensions [83], yet it oversimplifies complex emotional experiences. Arousal and valence aren't exclusive or equally effective in distinguishing all emotions and this may also result in information loss. Models based on cognitive theories, acknowledging varied emotional responses to the same stimuli, present a potential solution. According to this theory user's emotional state is influenced by their behavior and context [84]. In the first step of emotion recognition, signal acquisition is done from CNS (EEG) and PNS (ECG, EDA, and EMG, etc.) in various emotional states. Then features are extracted from those signals, which are used as an input to various classifiers for segregating emotion mostly on the matrices of arousal and valence. Stress and cognition-related classifications also employed the same framework. Some of the emotion, stress, and cognition studies are related to source localization. For these various statistical analyses are used.

The majority of the papers focus on a moderate number of subjects, typically ranging from 10 to 50 participants. This tendency could be attributed to the proximity to the empirical threshold value of the central limit theorem [85]. Within the scientific community, female-oriented research lacks a lot [86] and this is also noticeable here. Despite the inclusion of both female and male participants in certain studies, there are only 2 papers specifically focusing on physical activities carried out exclusively by females [22], [58]. Further research is needed to fill the gap in comparing CNS-PNS interaction studies between females and males. It has been seen that user-reported information may not accurately reflect the user's true state. Psychophysiological measures, on the other hand, reveal a more authentic representation of the user's actual condition. The primary challenges with psychological measures involve intricate arrangements of equipment, analysis of signals, and the need for a regulated environment. However, the benefits of psychophysiological analysis outweigh the drawbacks.

Some papers have utilized multiple modalities because they may provide richer information and can act in complementary roles against each other. This may also be the reason for getting better classification accuracy in multimodal cases compared to single physiological signal. The utilization of various combinations of features and classifiers can contribute to the enhancement of accuracy in assessing various psychophysiological states. By exploring diverse sets of features and classifier configurations, the accuracy of the classification process can be significantly improved. The selection of the feature extraction technique is dependent on the signal type and its inherent phenomenon. The utilization of time-frequency domain features is currently limited, indicating a potential avenue for future exploration. These types of features capture how the frequency content of signals changes over time, providing a comprehensive representation essential for analyzing non-stationary bio-signals. Given the nonlinear nature of physiological signals, there is a growing need for increased focus on nonlinear analyses in future studies.

Some of the popular ML-based classifiers used in these studies are SVM, LDA, RF, and K means clustering. The selection of a suitable classification algorithm is primarily driven by the specific bio-signal and application at hand. As the utilization of ML and artificial intelligence tools continues to grow, the integration of advanced DL methods becomes increasingly viable. Most of the articles here employed statistical analysis. The choice between statistical analysis and ML depends on the specific research question, data characteristics, and desired outcomes. In some cases, a combination of both approaches may be beneficial, where statistical analysis provides rigorous inference and ML techniques offer predictive power and pattern recognition capabilities. Albeit this type of technology holds promise for applications like psycho-physiological understanding, health support, and customer satisfaction enhancement, it also sparks concerns about personal privacy and public safety. The ethical questions arise from its ability to monitor, analyze, and interpret emotions with subjective profiling without consent, impacting personal sovereignty, integrity, and data credibility. Some privacy-preserving learning approaches such as Federated learning [87], Homomorphic Encryption-based Learning [88], Secure Multi-Party Computation (SMPC) [89] can be explored in future.

Secure anesthesia is attained through employing sophisticated techniques to assess the patient's condition throughout various stages of the surgical procedure. Under general anesthesia, a patient's condition is delineated by three primary facets which are interlinked, namely hypnosis, analgesia, and muscle relaxation. All of these three aspects may be understood through the interaction of EEG, PPG, and EMG signals [90]. Recent advancements in Large Language Models (LLMs) demonstrate promise in signal-to-text processing. Integrating LLMs unveils insights into CNS-PNS interaction, transforming physiological signal analysis through natural language processing, especially in the field of psycho-physiological disorders. The intricate interactions among various CNS and PNS-originated bio-signals generate artifacts among themselves. For example, EMG and ECG artifacts can be found in EEG signal [91]. Advances in affective neuroscience have greatly progressed in elucidating the impact of signals originating from the PNS on CNS-originated signals. One of its examples is the development of EEGLAB toolbox which has been used in many literatures to remove various PNS-originated artifacts from EEG [92]. However such kind of toolbox for PNS-originated signals has not been used in any of the literature. ANSLAB is such a toolbox that can be used for PNS-originated signals in future studies [93].

In studies related to sleep, numerous potential applications are rooted in the coupling of the CNS and PNS, either directly or indirectly. In the wearable tech market, enhancement of sleep scoring involves combining ECG-derived ANS features with EMG, EEG, PPG, and motion data. This helps in more accurate sleep stage assessment [94], [95]. During deception, simultaneous changes may be observed in brain activity along with heart rate, pupil diameter, and skin conductance. So, for automated lie detection, CNS-PNS interaction may provide a lot of improvement [96]. This type of neuro-ergonomics study has the potential to enhance sports performance as well. Combining EEG and EMG with additional sensors like an accelerometer to track the movement of the head, and a pulse oximeter for measuring HRV presents significant scope for monitoring biofeedback training for athletes [97]. Combining various modalities not only allows for a more immersive and engaging user experience but also facilitates the creation of adaptive virtual reality (VR) environments, particularly when continuous biofeedback is essential [98]. In the future, advanced motor imagery-based-BCI will be able to gain control of motor vehicles swiftly during emergency braking. For this purpose, BCI should be reliable and faster compared to PNS transmission in transmitting particular neural commands for braking. Implementing such applications requires a profound understanding of the CNS-PNS interaction [99].

The majority of interactive studies rely predominantly on subjective evaluations. It is essential to incorporate objective methods for measuring diverse psycho-physiological states. A hybrid approach that combines both techniques can prove beneficial, with each method complementing the other. The literature reviewed has primarily employed a small number of datasets or experiments related to daily life activities. This is justifiable considering the rarity, subjectivity, and diversity of atypical activities in the real world. Many researchers obtained their datasets in controlled environments. Meanwhile, ambulatory recordings and synthetic data generation can offer a partial solution, a more sustainable long-term solution is imperative.

Conventional signal processing techniques demonstrate mathematical accuracy with smaller datasets but experience a decline in performance as the dataset size grows. Conversely, DL algorithms perform more effectively with larger datasets, benefiting from their inherent data-hungry nature. The simultaneous interaction of the brain and PNS innervated organs should be explored more using graph theory-based approaches such as brain connectivity [100]. This facilitates in characterizing the stationary pattern of EEG, which may not be elucidated through simple linear techniques [101]. Functional connectivity gives us a better temporal understanding of various brain functions [102]. However, effective connectivity assesses how the functioning of a specific brain region impacts other distinct brain areas [103].

The utilization of wet electrodes demands the application of an electrolytic gel to improve conduction, but this can be uncomfortable for participants. Therefore, in scenarios requiring real-time acquisition dry electrodes should be preferred [104]. The interface quality depends on the configuration, placement, and geometry of the electrodes. Closeness to the nerve fiber and a small electrode site size lead to exceptionally high interfacial selectivity. So multi-channel intra-fascicular microelectrode may be a good option for better PNS neural interface [1]. The determination of the appropriate no. of recording electrodes needs more exploration [105].

V. CONCLUSION

This comprehensive review conducted a bibliometric analysis of selected papers published between 2008 and 2023 to investigate the utilization of different modalities in studying the interaction between the CNS and PNS. All the 629 articles are subjected to a rigorous selection process known as PRISMA. After that, a meticulous quantitative and qualitative study is done from various aspects. According to the knowledge, this review is the first literature to consolidate various types of interaction between EEG and other physiological signals in diverse psychophysiological scenarios. The review provided a thorough analysis of the prominent research trends in the field of cognitive neuro-ergonomics.

It illustrates the diverse interaction domains of bio-signals associated with various psycho-physiological states through the analysis of 61 articles. Additionally, it presents the details on subject information, stimulation modalities, data acquisition protocols and devices, application types, useful features, and analytical approaches.

It revealed a growing trend in publications in this field over the past ten years, specifically after the year 2020. The majority of the studies employed EEG band power and heart rate variability parameters to assess the interaction between the CNS and PNS in diverse psychophysiological contexts. The majority of the approaches primarily concentrated on improving the recognition of psychological states or determining the specific brain regions that play an important role in particular physical or mental states. Most of the methods utilized a combination of features, classifiers, and statistical analysis to achieve their goals.

This comprehensive study indicates that past research did not adhere to a standard experimental framework, leading to notable variations in the size of the sample, age, gender, and duration of the session. This lack of uniformity complicates the comparison of results across different contexts. A fundamental approach in constructing a credible theory involves validating prior findings using a more generalized dataset. This process seeks to address questions regarding the performance of existing theories across various societal contexts, modalities, and experiences.

Finally, the utilization of the DL algorithms and hybrid fusion (combination of sensor and decision level fusion) for large and high-dimensional data may be a new arena for exploring the characterization of the CNS-PNS interaction. Another dimension in which future studies can be done is the interaction of CNS and PNS in various cases of physical or mental disorders. Assessing the various proposed methods' adherence to standards and regulations is an important prerequisite for the potential mass application of such research. This involves a comprehensive examination of the regulations and standards from the design phase. The findings from the systematic review may provide valuable insights for the next generation of researchers interested in future studies related to bio-signal interaction.

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