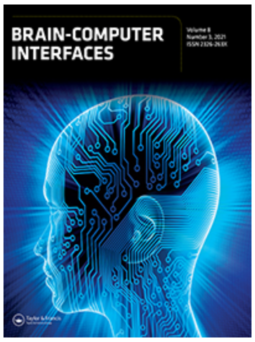

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Brain-Computer Interfaces

ISSN: (Print) (Online) Journal homepage: https://www.tandfonline.com/loi/tbci20

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BRAIN-COMPUTER INTERFACES
2021, VOL. 8, NO. 3, 82–91
https://doi.org/10.1080/2326263X.2021.1935124

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ABSTRACT

The development of Brain-Computer Interfaces (BCI) gathers experts and specialists in various fields, such as engineering, computer science, medicine, or cognitive neuroscience. Each of these disciplines has specific terminology, which makes mutual understanding and research collaboration difficult. The IEEE P2731 working group aims to improve communication between BCI researchers by developing a functional model and standards for terminology that can be used as a common description framework for all the involved knowledge fields. This work focuses on the vocabulary of mental processes involved in BCI communication and describes their role in a Functional Model that considers their influence on BCI performance. Finally, it presents potential uses of the proposed model.

ARTICLE HISTORY
Received 5 January 2021
Accepted 3 May 2021

KEYWORDS
BCI; mental task; individual differences; cognitive processes; human factor

1. Introduction

This paper describes the role that psychological factors play in the Functional Model of Brain-Computer Interface (BCI) developed by the IEEE P2731 working group. While other papers in this special issue are devoted to objective, measurable phenomena, this paper deals with psychological states which have traditionally been described through a combination of subjective accounts combined with observable behavior that is not necessarily measurable. One goal of BCI-based science is to quantify psychological states by associating them with physiological changes that can be measured by electrical activity in the brain. Yet, a number of ambiguities exist in disciplines based on BCI. Some of these are practical, and some derive from factors which are specific to psychology.

Since its founding BCI-based science has lacked three critical elements: an abstract model of its apparatus, a set of universally applied definitions of its objects of study, and a specification of common data formats for the results of experiments. This state of affairs has hampered the advance of BCI-based science and its technological applications because it is either difficult or impossible to combine data from different experiments. The IEEE P2731 working group is addressing the first two gaps, and it intends to address the last in a later project. Its aim is to provide a common, global framework for sharing data derived from BCI experiments.

This paper is organized as follows.Sections II offers a brief history of the role psychology has played in BCI-science.Sections III describes how psychological states correlate to physiological processes measured by BCI. Sections IV offers an overview of how BCI research has broadened knowledge of mental processes. In Sections V and VI, the authors describe how psychological factors have been incorporated into the IEEE P2731 Working Group's Functional Model of BCI developed by the working group and provides examples of practical applications. The paper concludes with a summary of standardization of psychological terminology and physical correlates will facilitate the advance of BCI-based science and technology.

1.1. History of BCI

Experiments by German psychiatrist Hans Berger, in the early 20th century, revealed that healthy brains produce regular electrical oscillations and other signature waveforms that can be measured through electrodes. These phenomena, popularly known as brain waves, correlate with characteristic physiological and psychological states [1]. While popular conceptions of brain waves often overstate or oversimplify the

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correlation of electrical activity with particular psychological phenomena, many associations have been validated, and advances in neurophysiology, data analysis and sensing technologies have enabled an ever wider range of scientific data and practical applications for BCI, including the direct mental control of external actuators [2].

One of the earliest discoveries in BCI-based science is notably Berger's identification of alpha, beta, theta, and delta rhythms during the earliest EEG recordings in the 1920s [3]. Each rhythm corresponded to an observable psychological state when neural oscillations within a characteristic frequency band were observed. During the course of the 20th century, Berger's bands were refined considerably, and researchers discovered a fifth band of higher frequency oscillations named gamma [4]. Along with singular neural events that will be discussed below, the five 'classic' frequency bands summarized in Table 1 have been broadly utilized in scientific and practical applications.

It should be noted that improvements in sensors, neurophysiological models, and especially the extraction of meaningful data with machine learning have accelerated progress in BCI. New techniques have revealed an increasing number of new waveforms, subcategories, and, more importantly, unexpected relationships among well-known waveforms [9]. The discussion below will touch on some of these newer and relatively unexplored phenomena, but they are too early to incorporate into the P2731 Functional Model, which is intended for immediate practical applications.

However, we note that the P2731 Functional Model is designed to flexibly evolve with the disciplines it serves. While the classic model and its definitions still dominate BCI-based activities, and it clearly has explanatory power today, advances in our understanding of neural oscillations and other neural events may one day require a modified or new framework for categorizing electrical activity in the brain and its psychological correlates.

Table 1. Main categories of neural oscillations with psychological correlates.

CATEGORY	FREQUENCY RANGE	PSYCHOLOGICAL STATE
Delta	0.5–4 Hz	Sleep [5].
Theta	4–8 Hz	Exploration, consolidation of spatial memory [6,9].
Alpha	8–12 Hz	Eyes closed, wakeful resting state [7].
Beta	12–30 Hz	Alertness, stimulus assessment, decision making [8].
Gamma	> 30 Hz	Synchronization of movement, memory consolidation, coordination of different cerebral regions.

2. Categories of stimuli

When measurements of electrical activity in the brain began in the 1920s, it was by no means given that subjects would respond consistently to stimuli and that these subjects will form identifiable classes. Time has revealed variation in neurological responses among individuals and even within the same individual. Though most human brains share sets of identifiable processes, some are not amenable to BCI, and much remains to develop a psychoneurological taxonomy that is comparable to physical anatomy in its accuracy and universality. Thus, researchers have been able to make strong psychological associations with some, but by no means all, physiological signals. This special issue focuses on the set of signals which can be reliably associated with psychological states and are consequently useful for practical applications of the P2731 Functional Model.

The stimuli detected by BCIs can be described as exogenous and endogenous. Exogenous BCI relies on events which have been programmed by experimenters, e.g., flashing lights that hypothetically will provoke a consistent reaction within and across BCI subjects[1] [10]. Endogenous systems detect physiological activities occurring spontaneously within the brain, either as part of its internal regulation, self-initiated cognition or in response to its overall environment. As we shall discuss below, the endogenous category includes signals psychologically generated by subjects in response to verbal requests by researchers rather than direct stimuli.

Although exogenous stimuli are provided by experimenters, it is possible to study reactions that subjects self-produce by request or due to internal changes such as interest or fatigue. For these, a signal processing algorithm in the transducer module recognizes changes that a targeted selection of stimuli produces in the user's nervous system. In contrast, endogenous systems (also called active interfaces), detect mental states that are unprovoked by direct stimuli. They rely on the fact that imagined movement – suggested but not performed – or the willingness to perform a specific action causes changes in electrophysiological [11] and metabolic [12] indicators of brain activity.[2]

Regardless of the type of physiological phenomenon used, psychological factors influence the BCI control process. In fact, there are a range of inter-and intra-individual factors, whose role in BCI performance has been proven in numerous studies [2,13–15]. Therefore, the functional model proposed by the IEEE P2731 working group accounts for the role of mental processes as modifiers of BCI performance [16].

Exogenous systems can be categorized as passive, as in steady-state evoked potentials (SSEP) [17], or reactive. as in systems that detect event-related potentials (ERPs) [18]. The interaction of various forms of sensory stimuli induces different physiological reactions. The stimuli can be exo- or endogenic, depending on whether the interface is passive [17], active [11], or reactive [18]. A specific variant of BCIs is adaptive interfaces that adjust to users' physiological and psychological state changes (Table 2).

In the case of passive interfaces, physiological changes in brain activity are evoked by stimuli from the user's environment. BCIs based on the steady-state evoked potentials effect use the association between the physical characteristics of the received stimulus, and the response in areas of the cerebral cortex related to the processing of this type of information. Stimuli properties like the rate of visual [17], auditory [19], or tactile [20] presentation cause an increase in the EEG signal's power for the same frequency in the occipital, temporal or frontal-parietal cortex. If several stimuli are presented at different frequencies, the frequencies corresponding to the unattended elements will be attenuated. Simultaneously, the frequency representing the target stimulus will have a higher power in the signal. In a typical BCI using visual stimulation, i.e., steady-state visual evoked potentials (SSVEP), stimuli are presented in the form of LED screens located in different areas of the visual field. The user fixes their gaze on the screen that displays a symbol corresponding to the activity they want to perform (Figure 1). Their choice increases the occipital electrodes' power for the same frequency as the selected screen's flickering rate [21].

Motor Imagery-BCIs often belongs to the category of active interfaces because they respond to changes in cortical activity related to movement-related thoughts (Figure 2). The user induces changes in, e.g., the power of oscillation in the sensorimotor rhythms (SMRs) [22] or the degree of oxygenation of brain areas [23] by simulating motor activity in their mind. Therefore, the reaction is endogenous, but the trigger signal comes from an external visual [24], auditory [25], or tactile [26] cue. For example, the user may think of movement after hearing a sound signal or try to move the cursor on the screen in the direction of a target placed in a 2-D [27] or 3-D [28] space.

In addition to active and passive BCIs, there is also an intermediate form called reactive systems. P300 BCIs are an example of this approach, which requires users to direct attention to the target while ignoring other elements. These interfaces use the P300 evoked potential, a singular waveform which can be registered about 300 ms after presenting an awaited stimulus (visual,

Table 2. A comparison of the main types of user interaction with the brain-computer interface.

Type of interface	Stimuli	Physiological state	Psychological state	Training time	Fatigue	Transfer rate	Acquisition methods	Example of a commercial solution
Passive	exogenic	steady-state somatosensory evoked potentials (SSSEP); steady-state auditory evoked potentials (SSAP); steady-state visual evoked potentials (SSVEP)	attention	short	high	high	EEG; MEG; ECoG; LFP	Blinker (BrainTech Sp. z o.o., Warsaw, Poland)
Active	endogenic	Event-related desynchronization (ERD); Event-related synchronization (ERS) of brain rhythms	motor imagery; mental rotation; mental calculations	long	low	low	EEG; MEG; EcoG; LFP; fMRI; fNIRS	RecoveriX (g.tec medical engineering GmbH, Schiedlberg, Austria)
Reactive	exogenic/	endogenic	auditory/visual/tactile P300 event-related potentials (P300-ERPs)				attention	short
high	high	EEG; MEG; ECoG; LFP	Unicorn Speller (g.tec medical engineering GmbH, Schiedlberg, Austria)					
Adaptive	exogenic/	endogenic	personalized mentaltasks	Fatigue,			frustration, attention	long
low	low	EEG	Unknown					

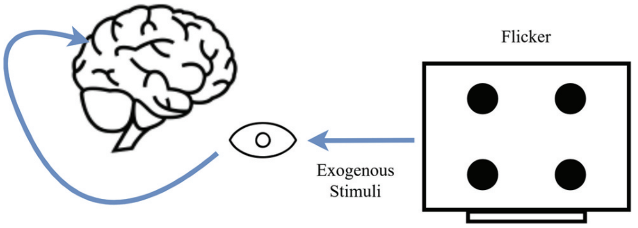

Figure 1. Stimuli for an SSVEP based BCI. The exogenous stimulus is captured by the visual system and defines a passive BCI.

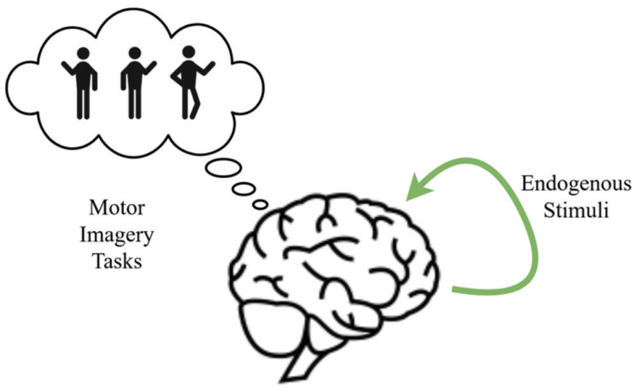

Figure 2. Stimuli for a motor imagery based BCI setting. The endogenous stimuli proceeds from neuromodulation of brain rhythms when simulating motor activity, which defines an active BCI.

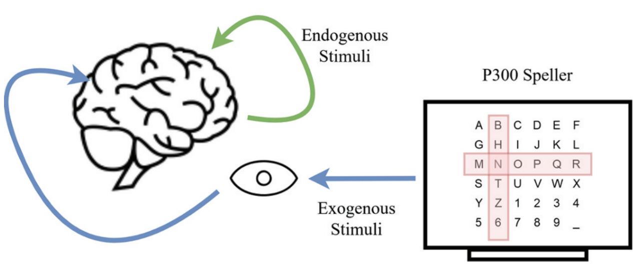

Figure 3. Stimuli for a P300 speller setting. The combination of both endogenous and exogenous stimuli defines a reactive BCI.

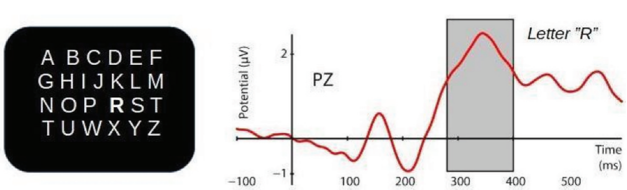

Figure 4. Amplitude increase about 300 ms after the onset of the oddball stimulus.

auditory, or tactile) or after directing attention to a new element in a set of known elements (see Figure 3). In most cases, reactive BCIs use a screen displaying rows and columns of symbols. Figure 4 illustrates how this system enables users who are unable to communicate to spell sentences. The user interface presents matrices of letters or other objects in a specific order, and users focus on elements of interest. This procedure allows the timing of each highlighted symbol to be assigned to a user's intention. The symbol on which the user has consciously focused evokes a higher amplitude of the P300 component than its neighbors [29].

In addition to screen-based stimuli, recent works have focused on developing more natural interfaces to augment or imitate human senses. For example, exoskeletons with force feedback [30] or vibro-tactile interfaces can reduce the required amount of training time for some users [31], and the combination with engaging feedback suggests that the principles of P300 based BCIs are optimal for many medical rehabilitation and recovery applications [32]. Nevertheless, considering the amount and variety of sensory data that a brain receives, the challenges of multi-modal sensing should be considered. For example, advanced analytic techniques may be required to make the collated data useful to other BCI components, e.g. the transducer and control interface. This challenge reflects the necessity of mapping disparate readings onto a computational model that accurately interprets the user's psychological state and/or intentions.

3. Psychological underpinnings of BCI

Although consciousness is a hallmark of human cognition, there are many categories of subjective awareness and competing schools of psychology to explain them. BCI is one of the primary tools used to probe mental activity, and it enables studies of cognitive neuroscience that would otherwise be impossible for ethical reasons. For the present purposes, we can offer four principles of psychology that underpin a BCI system:

(1) BCI science depends on voluntary and involuntary reactions to stimuli.
(2) Much of the brain's activity is inaccessible to subjective awareness.
(3) Some distinct psychological states such as surprise generate detectable physiological signals.
(4) Some psychological states are not crisply defined by subjective reports, but it is possible to categorize them with growing precision by combining physiological signals and behavioral observation with subjective reports.

Two approaches to BCI emerge from these principles. One focused on scientific inquiry, i.e., with the goal of seeking primary knowledge about mental processes, which uses BCIs as a probe that may or may not require conscious intervention on the subject's part. The second approach focuses on what it may be called biomedical engineering. It has therapeutic or practical goals, and it applies BCI to offer subjects direct mental control of virtual or physical actuators. Though it may work with little or no training on the part of subjects, it often resembles an acquired skill which the user improves with practice.[3]

3.1. Attention

Despite the fact that a human brain contains a massive amount of cells, studies using implanted electrodes have shown that a single neuron can play a detectable role in the formation of memories, decisions and movements [33]. Brain waves represent the synchronized activity of multitudes of neurons. At the base of these rhythms are 'action potentials' which represent the electrical signals of individual neurons. As the body's control center, the brain is responsible for critical decisions. How does it prioritize the constant flood of internal and external stimuli that trigger neural activity? The psychological state of attention is central to and yet dependent on the brain's self-management. The interdependency between neural activities and psychological states is a longstanding research endeavor and vast field of study which is summarized here.

Attention may be defined as a focused state of awareness. As discussed in the preceding paper on physiology,[4] and the previous section on P300-based systems, attention generates well-defined waveforms that can be detected through a variety of electrical and metabolic signals. Some physiological manifestations of attention are involuntary, e.g., SSEPs (Somatosensory Evoked Potentials), a process of entrainment wherein neurons automatically synchronize to ongoing rhythmic sensations. Another category of involuntary attention are singular waveforms that propagate in response to novelty. Along with the P300 spike, the C1/N1 waves that evoke visual discrimination [34].

Inhibition is another way of identifying attention on the neural level. From this perspective, attention may be defined as a process in which the neuronal response to sensations is either maintained or suppressed [35]. According to Jensen and Mazaheri [36], it is possible to predict a subject's aptitude at a task based on a decrease in the activity of neurons unrelated to its performance. For example, a task that employs the visual dorsal stream may be associated with an increase in the alpha power of the visual ventral stream. Because alpha waves are linked with inhibition, their appearance may serve as the physiological correlate of the psychological state of attention [37].

Involuntary attention often precedes conscious awareness. This result was unsurprising for sensory phenomena, but the discovery that a similar process governs motor phenomena provoked a philosophical crisis. In essence, a BCI senses the 'decision' to act – e.g., to move a hand – in the sensorimotor cortex before the subject becomes consciously aware of the decision [38].

With attention as a proxy for consciousness, the use of BCI has both resolved and provoked questions which were long confined to speculative theory, for instance, theories of consciousness common in philosophy and psychology. Attention also forms the basis of practical BCI applications which seek to give both healthy and disabled subjects the capacity to control external systems through focused mental effort. Attention is part of the brain's toolkit for constructing mental models that enable perception and interaction with phenomena at both physical and mental-psychological levels. Therefore, within the Functional Model of BCI, attention operates as one of the brain's primary interfaces with the engineered transducer module.

3.2. Global states

In the classic model where the brain operates within five frequency bands, neural oscillations range from 0.5–-120 Hz. It is now known that important rhythms occur below 0.5 Hz SCPs (Slow Cortical Potentials) [39], and significantly faster than 120 Hz HFOs (High Frequency Oscillations have been detected up to 500 Hz) [40]. However, these frequency bands are associated with phenomena that occur outside conscious awareness, such as memory consolidation, so at the time of writing, the psychological associations of these emergent frequency bands are indirect. In contrast the established frequency bands are associated with psychological states which are observable from both objective measurements and subjective reports.

3.3. Mental simulation

Interfaces based on mental imaging simulate a particular stimulus or class of stimuli without perception [41]. Mental simulation replaces perception with imagination supported by memory. The stimulus representation can be, for example, a mental representation of a sound [42] or movement [22]. The second type of mental simulation, known as motor imagery (MI), is widely used in SMR-BCI [43]. Sensations of clenching the right and left hand [44], the movement of the foot or the tongue [45], as well as the motor attempts [46], can be the object of motor imagery. At the same time, the same stimulus can be imagined in different ways and from various perspectives. In the case of movement, it can be a recall of bodily sensations during physical actions, such as muscle tension or a mental representation of a motor act seen from the observer's perspective [47]. Because MI is often used to control virtual or physical actuators, sensorimotor images are appropriate, particularly since they carry innate psychological intuitions such as left-right and up-down. However, there are practical reasons why sensorimotor imagery predominates in BCI applications.

The sensorimotor cortex is a well-mapped region on the brain's dorsal (upper) surface. It is thus accessible to EEG sensor arrays, which are both the least expensive and most comfortable form of BCI. Suggested MI can be communicated with relative ease from BCI operators to users. Sensorimotor images produce consistent, recognizable waveforms that are relatively easy to extract from the noisy data gathered by EEG electrodes and forms of signal capture.

Aside from MI, other cognitive tactics for obtaining reliable signals include mental rotation, word association, auditory imagery, mental subtraction, spatial navigation, and representations of familiar faces [48]. Some researchers have successfully tested a new category of 'high-level commands' that enlist multiple body parts and/or motions to articulate a wider range of expression within the system [49].

3.4. Emotions and motivations

Extrinsic factors such as discomfort can impact the success of a BCI intervention. Although important results have been gathered with fMRI and other platforms, EEG is preferable from the standpoint of psychology. Minimizing the set-up time, weight and intrusiveness of BCI apparatus contributes to the success of activities because fatigued, bored or uncomfortable subjects are less likely to produce usable signals [50].

Studies have also shown that internal psychological factors affect the quality – and thus the detectability – of physiological signals. While motivation is difficult to quantify, one study explored this factor in subjects who were either offered a monetary reward or not for correct choices in a P300 Speller. The P300 is a characteristic waveform generated by surprise, and it typically occurs when participants are shown a succession of images that contains an 'oddball' (see Figure 4.). Researchers found that payments evoked positive motivation and that highly motivated individuals produced higher amplitude waves than controls [51].

Other experiments [52, 53], were conducted to examine the effects of selected environmental factors on users' stress levels and the ability to detect that stress level from behavioral patterns. User interfaces were limited to simple peripherals, namely a mouse and keyboard. The challenges in estimating the stress level, i.e., a single affective state recorded in these studies highlights the issues a generalized BCI system would face in turning sensor inputs into reliable psychological identifiers while filtering environmental factors that negatively impact the user's psychological state. These would likely increase manifold in a general purpose BCI that applies multimodal sensory and user interfaces outside the controlled conditions of a laboratory.

3.5. Inter- or intra-personal variations

From the beginning of BCI research, observers noted significant inter-user variance in BCI performance [54]. This leads to the assumption that the effectiveness of BCI communication is affected by one or more sets of individual properties [2].

Inter- or intrapersonal variables including temperament [55], sense of agency [56], locus of control [57], and personality factors [58] can be used as predictors of BCI performance. Users with higher endurance [55], emotional stability [13,57] and confidence in their own agency/effectiveness [13,56,59] seem to achieve better control over BCI. However, the possibility of predicting BCI performance based on questionnaire results has been criticized [60]. Perhaps only by expanding research groups, the number of controlled variables, or online sessions helps understand what personal factors are essential for controlling BCI [2,61].

Psychological factors have been identified as important impediments to successful control of BCI. Studies have revealed that as many as 10% to 50% of BCI users have problems with sufficiently controlling the system [62]. For example, this means that the application is not under the user's control, or the BCI reacts unexpectedly in a large number of trials. Poor performance can also be related to anatomical and physiological factors [2].

Unfortunately, one of the groups which may experience the most difficulties in using BCI could probably benefit from the technology the most. In the case of people affected by severe neurodegenerative diseases such as atrophic lateral sclerosis (ALS), BCIscould be an alternative to muscular control of communication organs and devices. However, according to meta-analyses by Marchetti and Priftis [63], regardless of the type of brain signal used in the interface (i.e., SCP-, SMR-, or ERP-based), BCI performance remains low for ALS patients.

Although applying mild electrical stimulation to muscles (STM) while subjects are forming mental images shows promise [64],· no significant increase in the reported BCI effectiveness was observed in the analyzed time frame (15 years). Various factors may cause these results, but as some authors suggest, it may be related to attention or motivation deficits observed in ALS patients [65]. Therefore, focusing on the psychological condition of ALS patients may be essential to increase the potency of BCI as an assistive device.

One goal of the P2731 workgroup is to lay the foundation for standardized data formats that can be used to compare research results from different laboratories and to conduct meta-analysis.

4. Psychological model

The psychological elements of the functional model combine internal and external stimuli to assess how the subject's internal representation of their environment, along with emotional and cognitive states, impact their capacity to control an actuator or otherwise achieve the BCI system objectives.

According to the P2731 working group functional model, psychological factors influence the physiological processes detected by BCI and by extension the system's state. (See Figure 5 and subsequent articles in this special issue.) The first type of impact is related to mental mechanisms that cause change in the parameters of physiological signal parameters during BCI-assisted communication. For example, mental imagery of right or left-hand movement changes the power of signal oscillations from the sensorimotor cortex. Simultaneously, the intensity of modulation depends on the specific psychophysical characteristics of imagined movements. For instance, kinesthetic representations cause greater changes in sensorimotor rhythms than visual-motor representations [47]. The choice of the motor imagery mode may depend on the user's

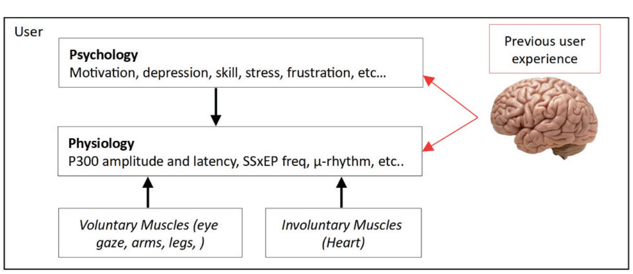

Figure 5. Psychological factors in the functional BCI model proposed by the P2731 working group.

individual attributes, such as handedness [66] or visualization capabilities [67], and the role these attributes play in the selection of imaging tactics needs to be recognized and standardized in experimental reports.

Qualities of the Control Interface also influence the mental processes involved in BCI communication. Esthetics and ease of use during the feedback presentation or encoder design results in differences in BCI performance and user experience satisfaction. Though related, these two qualities are distinct [24,68],, and they affect both the quality of experimental results and a system's potential for wider deployment.

Finally, a subject's reaction is influenced by constant and variable predispositions: there are inter- and intra-individual inconsistencies in mental processes which are expressed as psychological factors that impact the efficacy of BCI systems to achieve experimental or practical goals [2]. For example, users of P300-based BCIs may differ in endurance, and fatigue creates variations in the time needed to observe symbols flashing on the screen. Even the same subject may experience fluctuations of attentiveness during the same session, a situation that produces inconsistent results.

5. Application of the model

Several studies have shown the influence of both stable and variable psychological factors on BCI-based communication, but approaches to mitigating these factors differs among laboratories. For instance, according to Mladenović [69], currently, there are no common standards in BCI user training. Experimenters freely use varied techniques to maintain participant engagement and motivation, and they sometimes omit descriptions of the procedures used when they write research reports. Furthermore, existing training procedures do not sufficiently incorporate findings from other disciplines about the learning process [70]. Kübler and colleagues proposed a more holistic, user-focused approach to assessing the effectiveness of brain-computer interfaces [71]. According to the authors, assessment of BCI performance only by accuracy or information transfer rate does not contain the full complement of data relevant to evaluate results generated by different research centers. This view reflects a consensus among researchers in neurofeedback that information on the psychosocial factors and mental strategies used to generate results is essential to understanding experiments based on a subject's self-regulation of neural signals [72].

A standard model of BCI and glossary can support these and other efforts to improve the quality of research and advance practical applications of BCIs. The model proposed by the IEEE P2731 working group emphasizes the role of psychological factors and their influence on the physiological signals used in BCI applications. Personal characteristics and individual experiences of BCI subjects should be documented in procedure design, results reporting, and data sharing. Also, a unified terminology for describing sensory stimulation, mental processes, and individual differences might improve communication among BCI experts from different fields.

6. Conclusions

Although development of brain recording and signal processing methods is fundamental to improving the efficacy of future BCI systems, the impact of psychological factors on system results cannot be ignored. Brain-computer interfaces are based on interactions between psychological processes and their physiological correlates, so they are influenced by both subjective and environmental variables. Therefore, it seems crucial to include these dimensions in standardized formats when sharing experiment designs, scientific reports and databases.

BCI research is multidisciplinary, and it includes scientists from different theoretical and methodological backgrounds. Inclusion of terminology and research methods from psychology, cognitive science, neuroscience, signal acquisition or data processing requires developing a common language for specialists from these fields, and the expanding community of developers seeking to create practical applications for BCI. The development of a IEEE P2731 working group's standard BCI Functional Model and its associated glossary may help remove obstacles to expanding research perspectives in BCI and the expanding range of disciplines and emerging industries which rely on it.

Notes

1. The term 'subjects' is used when humans wearing BCI apparatus are passive participants in scientific study. The term 'users' applies when participants are attempting control of external actuators, e.g., digital or mechanical systems, through brain waves detected by BCI.
2. Please see 'A Functional BCI Model by the P2731 working group: Physiology' in the same issue for an introduction to the neurophysiology of BCI systems.
3. Please see 'A Functional BCI Model by the P2731 working group: Transducer' in the same issue for information about machine learning and other techniques for directly inferring a subject's intent.
4. Please see 'A Functional BCI Model by the P2731 working group: Physiology' in the same issue.

Disclosure of potential conflicts of interest

No potential conflict of interest was reported by the author(s).

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