Clinical Review

What Internal Variables Affect Sensorimotor Rhythm Brain-Computer Interface (SMR-BCI) Performance?

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Abstract

Description

In this review article, we aimed to create a summary of the effects of internal variables on the performance of sensorimotor rhythm-based brain computer interfaces (SMR-BCIs). SMR-BCIs can be potentially used for interfacing between the brain and devices, bypassing usual central nervous system output, such as muscle activity. The careful consideration of internal factors, affecting SMR-BCI performance, can maximize BCI application in both healthy and disabled people. Internal variables may be generalized as descriptors of the processes mainly dependent on the BCI user and/or originating within the user. The current review aimed to critically evaluate and summarize the currently accumulated body of knowledge regarding the effect of internal variables on SMR-BCI performance. The examples of such internal variables include motor imagery, hand coordination, attention, motivation, quality of life, mood and neurophysiological signals other than SMR. We will conclude our review with the discussion about the future developments regarding the research on the effects of internal variables on SMR-BCI performance. The end-goal of this review paper is to provide current BCI users and researchers with the reference guide that can help them optimize the SMR-BCI performance by accounting for possible influences of various internal factors.

Keywords

BCI adoption rates; amyotrophic lateral sclerosis (ALS); attention; brain-computer interfaces (BCIs); BCI accuracy; BCI literacy; BCI performance; depression; distraction; electroencephalography (EEG); event-related desynchronization (ERD); information transfer rate (ITR); internal variables; mental state; motor imagery; mood; motivation; neuroprosthetics; quality of life (QoL); psychological variables; sensorimotor rhythm (SMR); signal classification accuracy

Introduction

A brain computer interface (BCI) is a device that records and translates the user's brain activity into various command signals, thus bypassing muscle activity and allowing direct communication between the brain and various devices. Guger et al. defined BCIs as "communication systems that allow people to send messages or commands without movement."[1] Electromagnetic brain activity for BCI control can be recorded by a set of sensors when using magnetoencephalography (MEG), by a set of electrode arrays placed on the scalp when employing electroencephalography (EEG), as well as by electrode grids placed directly on the cortical surface when utilizing electrocorticography (ECoG).[2] **Figure 1** demonstrates these methods of recording electromagnetic brain activity. We limited the scope of this review article to the BCIs driven by electrical signals that are recorded non-invasively, as this is one of the BCI types that is currently the most suitable for application outside the controlled laboratory settings. The recorded brain activity is further processed by the BCI according to a pre-defined fixed or changing ("adaptive") algorithm that translates the acquired signal in real time into the computer commands. This allows control of the devices that might be placed both within or outside of the BCI user. **Figure 2**

Figure 1. Recording of magnetic (MEG) and electric (EEG, ECoG) brain activity that can be used for Brain-Computer Interface (BCI) applications. Left: Example of magnetoencephalography (MEG) at BioMag Laboratory, Helsinki University Central Hospital; Middle: Example of electroencephalography (EEG) at the Department of Biophysics, Vilnius University; Right: Example of electrocorticography (ECoG) at the Comprehensive Epilepsy Surgery Center, AdventHealth Orlando. (Photographs courtesy of the authors.)

depicts this closed-loop system for the operation of a BCI.

Among various electromagnetic signals that can be detected and utilized for BCI control, sensorimotor rhythm (SMR) is one of the most common. Sensorimotor rhythm-based BCIs (SMR-BCIs) (also referred to as motor imagery BCIs - MI-BCIs) can detect the event-related desynchronization (ERD) in the electromagnetic signal recorded from sensorimotor areas of the brain during the motor imagery task. **Figure 3** provides examples of motor imagery-related responses during a motor imagery task by using different signal recording modalities. SMR-BCIs hold great potential for improving clinical outcomes in patients with compromised motor function. Indeed, the advancement of motor rehabilitation is the classic goal of SMR-BCI research.[3] A comprehensive review of SMR-BCI studies suggests EEG-based SMR-BCI intervention is a promising rehabilitation
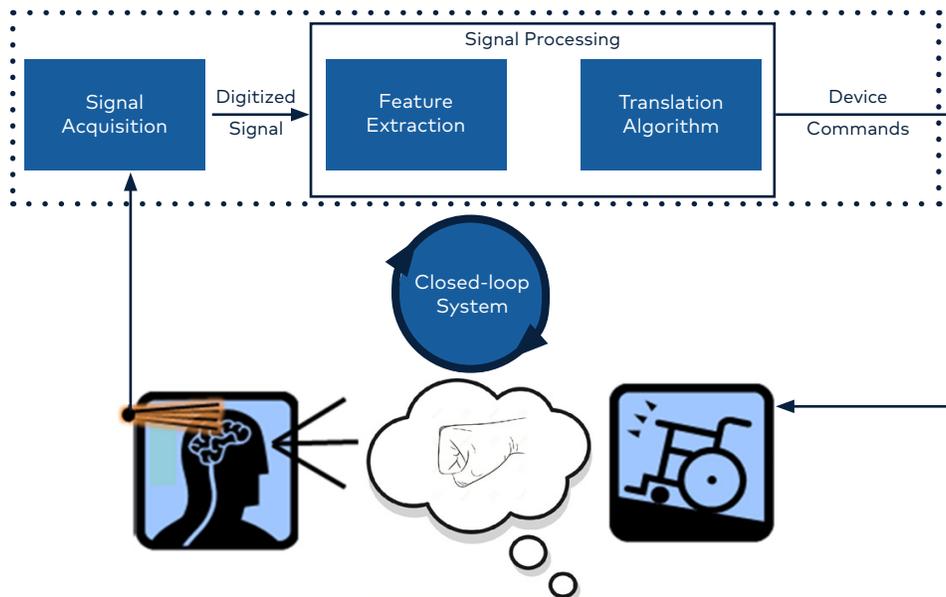
Figure 2. Brain Computer Interface (BCI) system set-up. A task (for example, imagining closing and opening the hand) triggers specific brain activity within the BCI user (for example, event-related desynchronization) that is detected by EEG, MEG, or ECoG. BCI processes this acquired signal, extracting relevant features according to a predefined or "adaptive" algorithm. The BCI translates the detected features into a device command (for example, a forward wheelchair movement). Device commands commonly involve directional control.
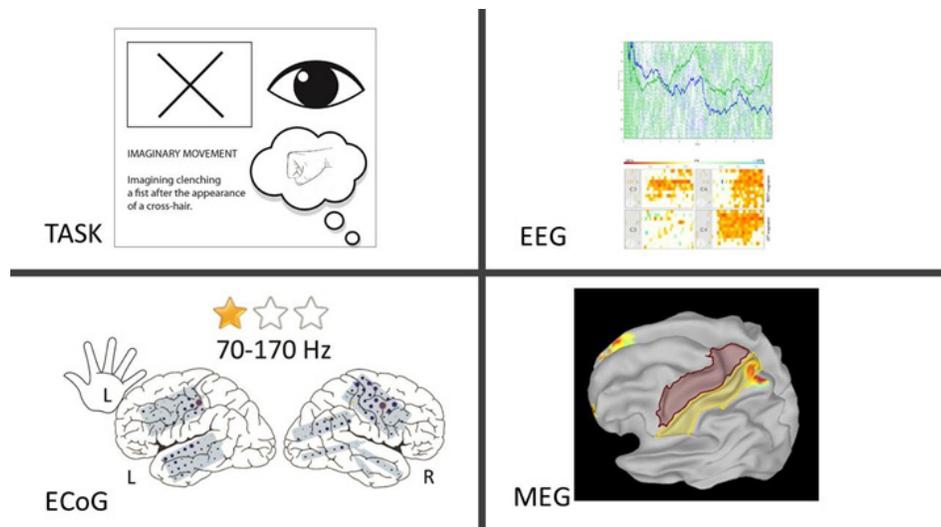
Figure 3. Examples of motor-imagery related responses during the motor-imagery task (upper left), recorded with different imaging modalities. Motor imagery is defined as "a mentally rehearsed task in which movement is imagined but not performed."[10] Motor imagery tasks may include practicing making a fist, walking, or grasping an object. Motor imagery is associated with the generation of electromagnetic brain activity. This brain activity for BCI control can be recorded by a set of electrode arrays placed on the scalp when employing electroencephalography (EEG, upper right), by electrode grids placed directly on the cortical surface when utilizing electrocorticography (ECoG, lower left), as well as by a set of sensors when using magnetoencephalography (MEG, lower right).[2] (Images courtesy of the authors.)

approach for upper motor function rehabilitation after stroke.[4] Moreover, in individuals with compromised skeletal and/or motor system function (such as paralysis and amputation), a BCI may be used as a substitute to overcome functional deficit.[5] Directional control is another common SMR-BCIs application for the manipulation of a cursor on a screen used, for example, for the steering of a wheelchair[6] or the control of a robotic neuroprosthesis.[7,8]

With continued development, a future becomes possible where BCIs are found throughout the surrounding environment and utilized in everyday activities by both healthy users (e.g., for augmentation of existing function) and disabled users (e.g., for functional improvement or total replacement of function) alike. We can refer to such BCIs as "ecological." To allow for such ecological SMR-BCI implementation, it is imperative to understand how SMR-BCI performance is influenced by the user's environments: both internal and external. Indeed, the performance of a SMR-BCI is largely determined by the efficacy of the user, the BCI itself and the operational conditions. The importance of accounting for the effects of these factors is crucial for SMR-BCI performance optimization, and thus for the future proliferation of BCI use

in a real-world ("ecological") context. For this article, internal variables are defined as those factors largely originating from within the SMR-BCI user. External variables, on the other hand, are identified as those elements that mainly reside within the SMR-BCI itself or exist beyond the SMR-BCI user. It should be noted that these working definitions of internal and external variables are simply operational and are used for this paper. Variations on these terms are found elsewhere. In some circumstances, internal and external variables, defined as such here, can be highly intertwined and used interchangeably, for example, distractibility (originating within the user) and distractors (originating outside the user). Due to the large number of internal variables for consideration, we have limited the scope of this review article to only focus on the effect of internal variables on SMR-BCI performance. We have also prepared a systematic review of the effect of external variables on SMR-BCI performance in a sister article.[9]

Multiple studies have attempted to mimic and isolate internal variables, which may affect any metric of SMR-BCI performance, such as signal information transfer rate (ITR), correct response rate (CRR), adoption rate, classification

accuracy and reaching target accuracy.[1,6-8,11-13] (for more details, see **Table 1**).

The goals of our current review paper are the following: (1) To summarize and critically evaluate the existing body of knowledge about the factors affecting BCI performance by critically examining the effects of internal variables on SMR-BCI; (2) To colligate main predictors of BCI "literacy"; as well as (3) To discuss limitations and propose further directions of "eco-

logical" SMR-BCI research along with other possible factors that may or may not affect the SMR-BCIs' performance when presented within an "ecological" real-world context.

1. Internal Variables and Their Effect on SMR-BCI Performance

In this article, we define internal variables as elements, that to the major extent, originate from within the SMR-BCI user. They include,

Table 1. Summary of Internal Variables Affecting BCI Performance.

Internal Variables	Referenced Studies	Effect on BCI Performance	Details
1.1.1 Motor Imagery and Hand Coordination	Bian et al. (2018);[14] Halder et al. (2011);[15] Hwang et al. (2009);[16] Mashat et al. (2019);[17] Scherer et al. (2015);[18] Silva et al. (2020)[10]	Positive effect	Repetition of a simple motor imagery task can substantially improve sensorimotor rhythm generation. Motor imagery task complexity is directly related to the degree of SMR-BCI performance improvement.
1.1.2 Attention and Motivation	Botrel and Kubler (2019);[19] Cho et al. (2016);[20] Emami and Chau (2018);[21] Friedrich et al. (2011);[11] Geronimo et al. (2016);[22] Guger et al. (2003);[12] Guger et al. (2015);[23] Guger et al. (2000);[24] Hammer et al. (2012);[25] Hammer et al. (2014);[26] Jeunet et al. (2016);[27] Kleih and Kübler (2013);[28] Kleih et al. (2011);[29] Leeb et al. (2007);[30] Meng et al. (2018);[31] Nijboer et al. (2010)[13]	Positive effect	The performance level of concentration strength accounted for a proportion of SMR-BCI performance variation or insignificant positive association. Strong positive correlation between SMR-BCI classification accuracy and the "challenge" and "incompetence fear" motivational components. Intrinsic motivation was not associated with SMR-BCI performance in a consistent manner. High fatigue level significantly impaired the subjects' motor imagery EEG separatability.
1.2.1 Quality of Life	Nijboer et al. (2010)[13]	No effect	No significant relationship was observed between SEIQoL-DW scores and SMR-BCI counting accuracies.
1.2.2 Mood	Atassi et al. (2011);[32] Botrel and Kubler (2019);[19] Dryden et al. (2005);[33] Jeunet et al. (2015);[34] Nijboer et al. (2010);[13] Patten et al. (2003);[35] Thomschewski et al. (2017)[36]	Nature of an association unclear	No significant relationship was observed between mood and SMR-BCI counting accuracy. Strong predictive model based on a personality profile. Positive association between mood improvement, the duration of the study and SMR-BCI control mastery of confidence levels. Relaxation trainings did not improve SMR-BCI performance.

Table 1. Summary of Internal Variables Affecting BCI Performance. Cont'd.

Internal Variables	Referenced Studies	Effect on BCI Performance	Details
1.3 Neurophysiological Signals Other than SMR	Ahn et al. (2013);[37] Ang and Guan (2016);[38] Azab et al. (2019);[39] Bamdadian et al. (2014);[40] Belwafi et al. (2019);[41] Blankertz et al. (2010);[42] Dinares-Ferran et al. (2018);[43] Gaur et al. (2019);[44] Grosse-Wentrup and Schölkopf (2012);[45] Guan et al. (2019);[46] Joadder et al. (2019);[47] Olias et al. (2019);[48] Robinson et al. (2018);[49] Vidaurre et al. (2011);[50] Zhang and Wei (2019);[51] R. Zhang et al. (2015);[52] T. Zhang et al. (2016);[53] Y. Zhang et al. (2019)[54]	Positive effect	Inverse relationship between simple reaction time and information transfer rate. Spectral or network properties of resting state EEG activity are effective predictors of user's SMR-BCI performance. Adaptive and co-adaptive strategies may reduce the number of SMR-BCI users who cannot achieve SMR-BCI literacy. Novel particle swarm optimization algorithm significantly decreased classification error rate and number of channels compared to common spatial pattern methods.

but are not limited to, the BCI user's psychological, behavioral and biological status, along with mental state. This section is an overview of studies that examine the effects of these internal variables on SMR-BCI performance (for summary, see **Table 1**).

The question of internal variables and their effect on SMR-BCI performance becomes a topic of important discussion when a "BCI literacy" phenomenon is considered. BCI literacy is loosely defined as the user's ability to operate a BCI successfully. BCI literacy may be quantified as a classification accuracy of at least 80%.[12] However, values as low as 70% may be considered promising for the potential of future use.[50,55] One of the earliest estimates demonstrated only 19.2% of subjects achieved SMR-BCI literacy.[12] Later, Blankertz et al. reported that 8 out of 14 (57%) naive BCI users achieved a classification accuracy of at least 84%.[12,55] With the development of improved BCI interfaces and training paradigms, this proportion became greater. Several more recent estimates exist, claiming that on average roughly 75% of BCI users are SMR-BCI literate.[26,27,37,50]

Hammer et al. attempted to understand the phenomena of BCI illiteracy and performance variance amongst SMR-BCI users by identifying significant psychological predictors of SMR-BCI performance.[25] These authors concluded that fine motor skills, information processing and concentration degree are significantly positively associated with SMR-BCI performance.

1.1 Psychological and Behavioral BCI Users' Characteristics
1.1.1 Motor Imagery and Hand Coordination

As motor imagery is a key concept associated with SMR-BCI, it is considered an important internal factor influencing SMR-BCI performance. Motor imagery is defined as "a mentally rehearsed task in which movement is imagined but not performed."[56] Supplementary motor areas and the right middle gyrus are neural substrates of considerable motor imagery activity, task monitoring and working memory. Their activation implies the acquisition and recall of sensorimotor responses necessary for the operation of an SMR-BCI.[15] High aptitude SMR-BCI users demonstrate higher activation of the supplementary motor area during motor imagery and motor observation when compared to motor execution tasks.[15]

Repetition of a motor imagery task can significantly augment the performance of an SMR-BCI. Repetition can lead to considerable changes in sensorimotor rhythm generation,

resulting in improved SMR-BCI classification accuracy.[16] Furthermore, Scherer et al. noted the robustness of motor imagery practice's effect. The investigators described the capacity of individually adapted motor imagery task repetitions to improve SMR-BCI performance across a range of different tasks.[18]

The complexity of the motor imagery tasks may be associated with the user's SMR-BCI performance. For example, some studies have demonstrated a positive relationship between motor imagery task complexity and event-related desynchronization.[14,17] It is anticipated that this enhanced sensorimotor rhythm activity has the potential to contribute to improved SMR-BCI performance. Bian et al. demonstrated that trials with complex motor imagery tasks are associated with statistically significant improvement of SMR-BCI classification performance relative to trials with simple motor imagery tasks.[14] In trials with a complex motor imagery task, SMR-BCI users' mean classification accuracy of alpha and beta-band power spectral density increased by 5.58% relative to trials with simple motor tasks. Moreover, the highest increase of SMR-BCI classification accuracy observed in a single subject was 20%. Supporting these data, Bian et al. and Mashat et al. demonstrated an increase of up to 7.25% in SMR-BCI classification accuracy for a complex task relative to a simple task.[14,17] These are encouraging results for the application of an SMR-BCI in a complex, diverse real-world context filled with a variety of complex, simultaneously presented tasks.

1.1.2 Attention and Motivation
Attention
In a comprehensive literature review, Jeunet et al. identified attention as a crucial aspect of SMR-BCI performance.[27] A study by Geronimo et al. identified a significant positive association between attention and the SMR-BCI classification accuracy of patients with amyotrophic lateral sclerosis (ALS).[22] The investigators assessed the participants' attention capacity according to the ALS-cognitive behavioral scale. Attention was one of the four components of cognition in this scale. In particular, the attention domain was an important predictor of motor imagery quality. Quality was defined as the motor imagery signal robustness for a given electrode channel as calculated by

the standard difference between the average power spectrum in left and right motor imagery trials. Attention, as a component of overall cognition, could lead to an increase in signal fidelity of task-relevant EEG band power.[22] Botrel and Kubler further demonstrated that attention, defined as the ability to concentrate, is a significant predictor of SMR-BCI classification accuracy.[19] Supporting this assertion, more sophisticated virtual cursor control via SMR-BCI was achieved when the modulation of endogenous visuospatial attention was enabled for BCI study participants compared with similar trials without endogenous visuospatial attention.[31]

Although we describe distractors as an external variable in another SMR-BCI review article, its relationship to attention makes it relevant for discussion at this time.[9] We concluded that distractors have a significant positive effect on SMR-BCI performance.[9] This conclusion was supported by the finding that passive auditory distraction optimized mental imagery-based BCI classification accuracy. Additionally, intermittent small visual distractors altered mu and beta power of motor imagery-specific patterns but did not significantly alter SMR-BCI classification accuracy.

Distraction may be considered a state of the absence of attention. For this reason, it is anticipated that distraction is inversely related to SMR-BCI performance. Friedrich et al. demonstrated that auditory distractors had no adverse effect on cue-guided 4-class hybrid P300-SMR-BCI performance.[11] BCI performance was maintained during auditory distractors in all mental tasks. Emami and Chau further explored the influence of distractors with a study of the relationship between visual distractors and SMR-BCI classification accuracy.[21] Infrequent, small visual distractors altered mu and beta power of motor imagery-specific patterns but did not significantly alter SMR-BCI classification accuracy. Participants achieved a mean classification accuracy of 81.5 ± 14% for non-distractor trials, and 78.3 ± 17% for distractor trials.[21] These developments are promising for the everyday application of BCIs in noisy real-world contexts.

Earlier studies identified varying relationships between attention and SMR-BCI performance.

The user's concentration strength or degree of sustained attention, as measured by the Attitudes Towards Work test variable "performance level," accounted for approximately 19% of the variance in SMR-BCI performance.[25] Notably, a different study revealed a positive yet insignificant association between the predictive value of concentration ability and SMR-BCI performance.[26] A possible explanation for this discrepancy is that different metrics were used in these studies. Whereas the 2012 study by Hammer et al. used performance-based metrics to assess sustained attention, the 2014 research by Hammer et al. used self-reported metrics for the same purpose. [25,26] By virtue of its relationship with attention, motivation has the potential to influence SMR-BCI performance as well as to directly influence the subjects' attention towards the task at hand.

Motivation
Nijboer et al. defined motivation as "an impetus toward a goal for all current processes" and quantified it with a modified version of the Questionnaire for Current Motivation (QCM).[13] With the QCM, subjects self-evaluated their current motivation according to a Likert-type score of four internal motivational factors: mastery confidence, incompetence fear, challenge and interest. Their results did not reveal a clearly defined overall correlation between motivation and SMR-BCI performance. This led to the conclusion that motivational factors may affect SMR-BCI performance on an individual, case by case basis.[13]

Importantly, Nijboer et al. cautioned against the extrapolation of their study results in clinical patients to the general population.[13] The authors suspected that a different relationship would exist between the motivation of healthy users and SMR-BCI performance than the one determined in their study with clinical patients. Indeed, the study by Leeb et al. identified a strong positive correlation between the motivation or mental effort of ten healthy users and their SMI-BCI performance.[30] These findings are supported by Kleih et al., who observed a positive correlation between SMR-BCI classification accuracy and the "challenge" and "incompetence fear" motivational components of 41 healthy subjects.[29] This is consistent with other sources suggesting that motivation has been identified to have a significant positive correlation with SMR-BCI classification accuracy.[23,24]

It should be noted that the study by Nijboer et al. only contained ALS patients, no healthy subjects.[13] As opposed to healthy study participants, the ALS patients have a vested interest in the treatment and management of their condition. This deep awareness was reflected in the ALS patients' QCM scores, which demonstrated that the patients were highly intrinsically motivated.[13] Healthy individuals could, however, be extrinsically motivated (for example, by being provided with monetary compensation). Monetary compensation is a common practice to encourage subject participation. Offering a financial incentive would moderately provide extrinsic motivation for subjects to become involved with the study.[28]

Mediating factors can influence the performance of BCIs. The presence of mediating factors may explain the discrepancy in users' SMR-BCI performance by Guger et al.[12,23] In 2015, Guger et al. reported significantly higher SMR-BCI performance metrics than those of Guger et al. in 2003.[12,23] Motor imagery experiments were conducted with recoveriX—a BCI system for stroke rehabilitation. Further details on recoveriX are provided in **Figure 4**.

Five patients post-stroke (ages: 40, 61, 63, 66, 68) were trained with left and right motor imagery paradigms in 30 minute sessions.[23] When the BCI detected a brain response associated with imaginary hand/arm movement, a functional electrical stimulator was triggered to produce a real hand/arm movement. All five patients reached a very high BCI accuracy of 96, 96, 96, 98 and 99% within 25 training sessions. Recently, Cho et al. performed a similar motor imagery experiment involving recoveriX with one stroke patient.[20] Similarly to the previous study, this patient achieved a very high BCI performance accuracy of 96% within only 10 training sessions. One possible explanation for this variation in the number of training sessions needed to achieve high BCI performance accuracy is that the latter study only had a single patient. This individual may not have represented the average or normal user's SMR-BCI performance.

According to Guger et al. (2015), an important factor for such high BCI performance accura-
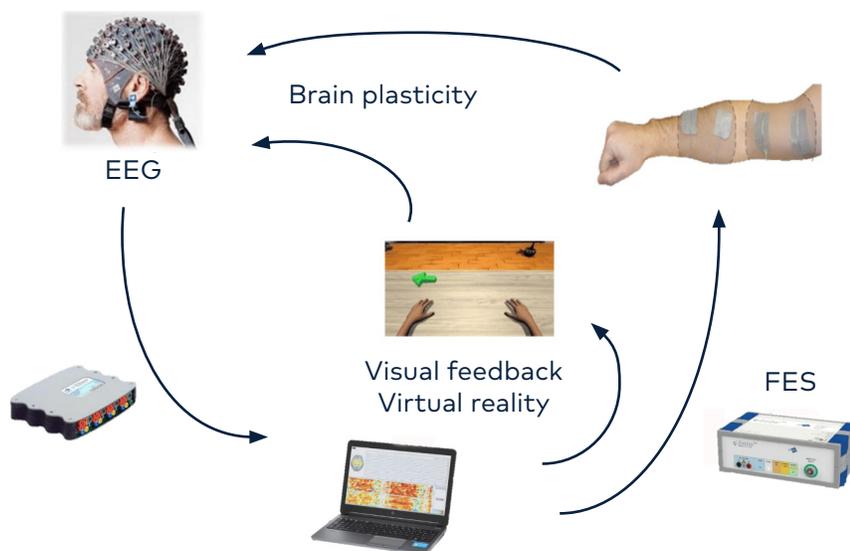
Figure 4. SMR-BCI system (recoveriX) for motor recovery in stroke patients. This complete hardware and software platform that is capable of recording and analyzing the EEG for rehabilitation consists of: an electroencephalography system (EEG), an avatar ("virtual reality") and a functional electrical stimulation (FES). The system provides the real-time, monitor-based virtual reality feedback (with an avatar and real-time brain activation maps). (Photographs courtesy of the authors.)

cies is the patients' motivation to participate in the training to improve their motor functions.[23] In their 2000 study, Guger et al. demonstrated that healthy controls can reach high classification accuracies within 6–7 training sessions of about 30 minutes.[24] In fact, three healthy students tested in this study achieved BCI performance accuracies above 95%. One subject even performed the first trial of 100% classification accuracy of all BCI studies.[24] The physical status of the participants of the 2015 Guger et al. study and the 2000 Guger et al. study served as a study in contrasts.[23,24] In the later study, 3 highly motivated students were selected to achieve these results. On the other hand, the earlier study involved recovering stroke patients. These SMR-BCI performance findings in a diverse patient population of highly motivated healthy subjects and afflicted patients offer promise for a higher future SMR-BCI adoption rate.

We will consider mental fatigue as the absence or diminution of motivation. Subjects with higher motivation should be able to delay the influence of mental fatigue. Conversely, subjects with lower motivation may prematurely succumb to mental fatigue's influence. It is anticipated that an indirect relationship would exist between mental fatigue and SMR-BCI performance. Indeed, Talukdar et al. supported this assumption.[57] The investigators monitored mental fatigue in eleven participants over the course of prolonged motor imagery sequences. High fatigue level significantly impaired the subjects' motor imagery-related EEG signal disctrimination.[57] The clear interpretation of EEG signals is crucial to optimal BCI performance. It is anticipated that decreased motor imagery-related EEG signal discrimination should interfere with the ability of an SMR-BCI to translate neural activity into motor machine commands. Future research is needed to confirm the correlation between decreased motor imagery-related EEG discrimination and SMR-BCI performance. These findings offer a potential electrophysiologic mechanism for decreased SMR-BCI performance with decreased motivation, as considered by mental fatigue.

1.2 Psychological Variables and Mental State
1.2.1 Motor Imagery and Self-Prediction of the SMR-BCI Competency

Formal analysis of psychological variables and mental state has attempted to support the assumption that these internal variables influence SMR-BCI performance. Spatial ability is associated with motor imagery, and therefore, potentially with the SMR-BCI performance. The men-

tal exercise of motor imagery facilitates neural network plasticity across several regions of the brain, thus developing spatial ability.[58] It was found that fine motor skills and the accuracy of information dissemination were responsible for 11% of SMR-BCI performance variance.[25] In addition to the effect on SMR-BCI variance demonstrated by the 2012 Hammer et al. study, the 2014 study by Hammer et al. confirmed the predictive role of visuo-motor coordination ability for SMR-BCI performance.[25,26]

Furthermore, Ahn et al. described that self-prediction of SMR-BCI competency in subjects with SMR-BCI experience shares a statistically significant relationship and moderate correlation with SMR-BCI performance.[59] Subjects' self-prediction of SMR-BCI competency improved over the course of repeated trials, even without feedback information.[59] In a later study, Rimbert et al. highlighted the limitations of self-prediction.[60] A subjective motor imagery questionnaire failed to predict the SMR-BCI performance of 35 healthy subjects.

Nijboer et al. tried to isolate several key internal variables that may affect SMR-BCI.[13] In particular, these researchers evaluated the influence of quality of life and mood on the performance of SMR-BCIs. Subjects were asked to control the vertical movement of a cursor in order to hit a target. The authors assessed SMR-BCI performance as a correct response rate (CRR), defined as the percentage of hit targets in a single session. Subjects used a 6 x 6 character matrix to copy the text of the sentence, "Franz chases in a completely shabby taxi across Bavaria." (This sentence in German is comprised of every letter of the alphabet, "Franz jagt im komplett verwahrlosten Taxi quer durch Bayern."[13] and serves as a German analogue of the English alphabet-containing phrase "The quick brown fox jumps over the lazy dog."). In order to compare CRR, the chance level of hitting a target (1/2 = 0.5) or select a correct character (1/36 = 0.027) must be considered. To standardize for chance, CRR was calculated into an information transfer rate (ITR). The findings reported by Nijboer et al. are discussed in the following subsections.[13]

1.2.1 Quality of Life
Quality of Life (QoL) provides a framework within which SMR-BCI training and implemen-

tation occurs. As a result, Nijboer et al. contend that this context may inform SMR-BCI performance and was the first to explore the QoL and MI-BCI performance relationship.[13] In their study, the authors used the Schedule for the Evaluation of Individual QoL Direct Weighting (SEIQoL-DW) to measure the subjects' QoL. Before completing the SMR-BCI portion of the study, all subjects demonstrated a QoL ranging from satisfactory to good (average SEIQoL-DW score before SMR training: 76.6). The results did not demonstrate a significant relationship between QoL and SMR-BCI performance. SMR-BCI performance accuracies were within the normal range even in those subjects who noted QoLs below average, further indicating that QoL may not have influence on SMR-BCI performance.

1.2.2 Mood
According to Nijboer et al., mood affects cognitive function.[13] Mood's influence on cognition leads to anticipation that subjects with a better mood would be more receptive to SMR-BCI training. In turn, it can be expected that mood would demonstrate a positive correlation with SMR-BCI performance. However, after evaluating the change in subjects' psychological state as they went through the SMR-BCI training and actual SMR-BCI control process, Nijboer et al. observed no relationship between mood and SMR-BCI performance.[13] Interestingly, the results showed an association between mood improvement and the duration of the study. The authors suggested that the reason behind this improvement in mood might due to the decrease in SMR-BCI control incompetence levels with the progression of the experiment. This change was accompanied by a corresponding increase of confidence levels in SMR-BCI control mastery, thus improving the mood of study participants.[13]

Botrel and Kubler supported the mood findings of Nijboer et al.[13,19] Four 30-minute relaxation trainings prior to a SMR-BCI session failed to improve the participants' SMR-BCI performance relative to groups who received one or no relaxation session.

The relationship between depression and SMR-BCI performance is highly relevant as disabled SMR-BCI users, due to their limited physical condition, frequently battle depression.[32,33,35]

Similarly to the results demonstrating no statistically significant effect of mood on SMR-BCI performance, Nijboer et al. showed no clear relationship between depression and subjects' SMR-BCI performance.[13] Later research supported this uncertain association.[36] In a study involving seven male patients with traumatic spinal cord injury, two patients demonstrated Beck Depression Inventory scores consistent with depression. These two patients reported the most problems with movement imagination, but statistical analysis could not confirm an association between depression and decreased SMR-BCI performance across all healthy controls and patients.[36]

In contrast to the findings of Nijboer et al., Jeunet et al. developed a strong predictive model for SMR-BCI performance based on the user's mood.[13,34] Through the use of a psychometric questionnaire, Jeunet et al. determined a personality profile based on moods, traits and emotional states.[34] More studies are needed to clarify the exact nature of the relationship between mood and SMR-BCI performance. Mood's effect on SMR-BCI performance is still not well understood. In the application of the Nijboer et al. findings, caution would be warranted.[13]

1.3 Neurophysiological Signals Other than SMR

Current literature suggests that physiological signals can be used to predict users' SMR-BCI performance.[37,38,40,42,45,47,49,50,52,53,61-63] For example, Grosse-Wentrup and Schölkopf could forecast subjects' inter-trial SMR-BCI classification accuracy by calculating the measured differences in gamma-power between two fronto-parietal networks.[45] These networks correlated with fMRI-identified neurological sites of focused attention and working memory, suggesting gamma oscillations are the neurophysiological signal correlate of these cognitive processes.[45]

Darvishi et al. identified simple reaction time as a significant predictor of subjects' future SMR-BCI performance.[61] Participants demonstrated an inverse relationship between simple reaction time and information transfer rate. In addition, researchers observed alpha and beta-wave activity of greater amplitude in this same participant population.[51]

However, a controversy exists regarding the effect of background electrophysiological brain activity on SMR-BCI performance. Bamdadian et al. used pre-cue EEG rhythms from different areas of the brain to develop a novel coefficient for predicting SMR-BCI classification performance.[40] Incorporating both spatial and spectral EEG signal information, Bamdadian et al. used this coefficient to predict users' SMR-BCI classification accuracy.[40] The results of this study suggested that users' higher frontal theta and lower posterior alpha activity led to improved SMR-BCI classification values. Contrary to observations by Bamdadian et al., a study by Ahn et al. described a moderately to strongly significant positive association between users' high theta and low alpha power with respect to SMR-BCI illiteracy.[37,40] Robinson et al. further explored the ability of resting state activity to predict SMR-BCI performance.[49] The results of their study suggested that entropy and gamma power from pre-motor and posterior areas as well as beta power from centro-parietal areas have a strong predictive correlation with SMR-BCI performance.[49]

Investigators have proposed alternative predictive elements of SMR-BCI performance.[38,42,50,52] Zhang et al. identified a strong correlation between the spectral entropy of eyes-closed resting-state EEG activity with inter-session SMR-BCI performance.[52] In particular, these authors selected the C3 channel as a potential biomarker of SMR-BCI performance. The findings demonstrated 89% effectiveness of an inter-session spectral entropy to predict the average SMR-BCI classification accuracy.[52] Zhang and Wei explored the role of channel selection on SMR-BCI performance.[51] Experimental results revealed that a novel particle swarm optimization algorithm significantly decreased classification error rate and the number of channels compared to common spatial pattern methods, which had previously demonstrated great promise.[51,54]

In a different study, Zhang et al. associated the resting-state EEG network with SMR-BCI performance.[52] Efficient resting-state network EEG activity qualities, such as greater mean functional connectivity, node degrees and edge strength led to enhanced user SMR-BCI performance. Conversely, increased characteristic path length was associated with decreased

user SMR-BCI performance. Characteristic path length is defined as "the average shortest path length between all pairs of nodes in the network".[52]

In addition, Blankertz et al. proposed a neurophysiological predictor of SMR-BCI performance.[42] The researchers derived this neurophysiological predictor from a two-minute recording of a "relax with eyes open" condition using two Laplacian EEG channels. This study observed only a moderately significant positive correlation between this prognostic technique and BCI literacy.[42]

Moreover, Ang and Guan determined an EEG-based adaptive strategy to reduce the variance between the SMR-BCI classification accuracies of calibration and feedback sessions.[38] In the adaptive strategy, a subject-specific model is continuously developed during these sessions based on EEG signals. This subject-specific model more accurately interprets users' EEG signals, thus improving SMR-BCI performance.[38]

Further studies support this adaptive strategy approach.[39,41,43,44,46-49] For instance, Joadder et al. developed a subject-independent performance-based EEG feature fusion algorithm in combination with machine learning for the classification of motor imagery signals into certain states.[47] This novel approach yielded a classification accuracy of 99%.

Prolonged calibration time is a barrier to widespread SMR-BCI use. Gaur et al. proposed an adaptive strategy of tangent space features-based transfer learning classification model for SMR-BCIs to eliminate lengthy training sessions.[44] The researchers defined transfer learning as "the process of applying the knowledge gained from one task to another related activity".[44] Expanding on a subject-specific multivariate empirical mode decomposition model, the researchers identified shared structures of the tangent space features among participants. This model was then used to evaluate the SMR-BCI classification accuracy of unseen trials. This novel tangent space features-based learning classification model yielded a similar SMR-BCI classification accuracy to other current adaptive classifiers such as subject-specific multivariate empirical mode decomposi-

tion-based filtering method, common spatial patterns on band-pass filtered EEG between 8 Hz and 30 Hz with linear discriminant analysis, common spatial patterns with covariate shift detection and adaptive learning, as well as filter bank common spatial pattern. Thus, the adaptive strategy of transfer learning techniques can be used to mitigate the problem of time-intensive training sessions.[44]

Olias et al. improved the widely used standard power normalization technique of EEG preprocessing through two new methods.[48] First, researchers presented a novel power-normalizing technique that is scaled independently of the observation trials. Second, the investigators proposed the application of an alternative shrinkage covariance matrices estimate that is based on normal statistical features. Together, these two methods yielded a significant improvement in SMR-BCI classification results.[48]

Co-adaptive SMR-BCI calibration advances this concept further, wherein both the algorithm of the SMR-BCI and the mental strategy of the user are mutually trained.[50] Co-adaptive SMR-BCI calibration has the potential to extend SMR-BCI literacy to new users.[50] With a co-adaptive SMR-BCI, naive users may be trained to operate an SMR-BCI within minutes of the first session. Moreover, SMR-BCI users, who previously failed to achieve adequate SMR-BCI control with an adaptive strategy, gained SMR-BCI literacy after fifteen minutes of feedback after the first run. These users demonstrated an improvement of SMR-BCI performance both during a session and between the first and last run.[50]

Overall, there is evidence that physiological signals are an effective predictor of users' SMR-BCI performance. Therefore, SMR-BCI candidate screening tools may include measures of their resting state activity, such as spectral or network properties, which would further the overall goal of widespread SMR-BCI application in everyday life by more readily recognizing those users of greater potential to adopt this technology successfully. Beyond the identification of potential SMR-BCI users, adaptive and co-adaptive SMR-BCI calibration strategies may reduce the number of SMR-BCI users who cannot achieve SMR-BCI literacy. Together, predictive biomarkers and adaptive strategies can expand the potential SMR-BCI user base.

Limitations and Future Perspectives

The study of the effects of internal variables on SMR-BCI performance is incomplete. Limitations exist within the previously described studies, and opportunities for future perspectives and development persist. In spite of the previously described motor imagery practice approach used to improve SMR-BCI performance, there remain users who are SMR-BCI "illiterate." Indeed, according to a study by Jeunet et al., only 70–90% of users are able to achieve SMR-BCI literacy.[27] Importantly, these authors have demonstrated that standard SMR-BCI training is insufficient for the SMR-BCI literacy improvement because it lacks adequate testing of spatial ability.[64] Spatial ability (such as two-hand coordination, sports or music practice) is an important factor of a successful SMR-BCI performance. The development of this aptitude is a significant component of an effective SMR-BCI training paradigm.[64] More research is needed to elucidate a motor imagery practice approach with a more effective spatial ability component.

In addition, the effect of motor imagery practice on SMR-BCI performance may be outpaced by simple motor observation. Halder et al. noted that brain function during motor observation could predict SMR-BCI user proficiency.[15] This finding is further supported by the higher number of activated voxels in the right middle frontal gyrus during motor observation rather than motor imagery or motor execution.[15] The effect of motor observation and its relationship with motor imagery are areas of future perspectives for the influence of motor imagery on SMR-BCI performance.

In the study by Nijboer et al., the authors identified several study limitations and areas for further inquiry.[13] The small (n = 6) study sample limited the significance of the findings. Furthermore, a larger testing population would allow for more demographic diversity to facilitate further inquiry into the relationship between numerous internal factors and SMR-BCI performance.

In addition, a larger sample size would allow for the incorporation of healthy subjects to serve as a control. ALS patients often have large electromyographic (EMG) artifacts because they cannot cease the symptoms of their condition such as coughing, swallowing or yawning during BCI experimental trials. These interrupted BCI trials have a low signal-to-noise ratio. This complicates the interpretation of study results because it is difficult to discern the signal of interest from the confounding signals. This factor of low signal-to-noise ratio can be controlled for with the presence of healthy subjects. Healthy subjects do not suffer from the described ALS-related symptoms and do not interrupt the BCI trials with the same regularity. As a result, healthy subjects demonstrate a higher signal-to-noise ratio than their ALS counterparts. The high signal-to-noise ratio of healthy control subjects would elucidate the SMR results of ALS patients, and thus would facilitate meaningful analysis.[13]

Nijboer et al. indicated that the influence of incentives on extrinsic motivation and SMR-BCI performance is another future area of research.[13] Healthy subjects may provide a wider range of QCM motivational scores than the intrinsically motivated ALS patients. The incorporation of healthy subjects would allow for a QCM data set with greater variance. This would facilitate the investigation into the impact of incentives on extrinsic motivation and SMR-BCI performance.

Conflicting evidence by Bamdadian et al. and Ahn et al. exists describing the nature of the relationship between alpha and theta electroencephalographic waves with SMR-BCI performance.[37,40] One possible explanation for this inconsistency is the locations of the neurophysiological recording sites, where the signal was sampled. For example, Bamdadian et al. selected frontal and parietal areas to calculate theta and alpha activity respectively.[40] On the other hand, Ahn et al. examined the prefrontal and central areas for theta activity.[37] Alpha activity was most strongly present in the occipital area. However, these sites may not fully explain the different findings in these two studies. More research is needed to clarify this question.

2. Next Steps

The domain of SMR-BCI performance optimization involves the SMR-BCI users. While not all variables have demonstrated a positive effect, internal variables have the potential to improve SMR-BCI performance metrics such as classification accuracy, information transfer

rate or task duration. Gaps of knowledge remain that may or may not affect the real-world application of SMR-BCI. Sample size is one of the most crucial aspects towards producing significance in a study. Here are some suggestions to investigate the effect of internal variables further:

2.1 Training Paradigm Development

During SMR-BCI training, subjects may become bored and frustrated with the repetitive nature of a simple task. As a result, the subjects' attention may wane during SMR-BCI training. Nijboer et al. suggested that an optimal training paradigm may involve a stepwise, progressively more complex task to maintain the selective and sustained attention of the subjects.[13] The exact nature of this increasingly complex task and the related protocols for it are another area that Nijboer et al. suggested for future research.[13]

2.2 Medication

Interestingly, Meng et al. explored the influence of caffeine consumption on resting state EEG and SMR-BCI performance.[62] Although caffeine consumption substantially decreased alpha and beta-band power in 26 healthy subjects, the researchers found no evidence of significant change on subjects' SMR-BCI performance relative to controls who did not consume caffeine.[62] Moreover, sugar consumption did not significantly influence either EEG resting state activity or SMR-BCI performance.[62] The relationship between frontal EEG activity and SMR-BCI performance has been further investigated by Zhang et al., who showed that subjects with an efficient fronto-parietal attention network activity perform better on SMR-BCI.[53]

Locked-in patients presently comprise many SMR-BCI users. Locked-in patients often suffer from conditions such as ALS, multiple sclerosis (MS) or spinal cord injury. As part of their treatment plan, SMR-BCI users may be prescribed antidepressants, opioids or benzodiazepines. Medical professionals must be aware of not only how medications affect not only their patients' physical being, but also their patients' ability to communicate with the world around them. Nijboer et al. suggested that a next step in the field of SMR-BCI research is an investigation into the effect of medications on SMR-BCI performance.[13]

2.3 Gender and Education

The gender of a user has been demonstrated to influence the classification accuracy of an SMR-BCI. Cantillo-Negrete et al. revealed that a gender-specific subject-independent design led to a significantly greater SMR-BCI performance than the performance observed in an SMR-BCI where gender is not considered.[65] Subject-independent design focuses on achieving BCI literacy while reducing SMR-BCI training requirements in the interest of the patient population who cannot meet this demand. For subject-independent design, researchers identify Common Spatial Patterns and log variance features amongst a group of subjects. Cantillo-Negrete et al. classified these data amongst two groups, males and females.[65] The investigators tasked both healthy subjects and stroke patients with imagining the opening and closing of the left and right hands. In almost all of the experimental conditions, the gender-specific SMR-BCI designs were associated with greater performance. However, the improved classification accuracy observed with a gender-specific SMR-BCI design was not always associated with the intended gender of the user.[65] A user's gender may influence the performance of an SMR-BCI, but more research is needed to more clearly elucidate this relationship.

The future goal of SMR-BCI use is for the widespread adoption of SMR-BCIs amongst all peoples. Ideally, no barriers for use would exist. Education is one potential barrier for SMR-BCI use. Education may be inversely related to comprehension of difficult instructions. As an emerging technology, SMR-BCI setup and operation involves numerous steps with sophisticated technologies. For this reason, it is anticipated that those who struggle to accurately operate the brain-computer interface may not experience optimal SMR-BCI performance. Moreover, Skrandies and Klein demonstrated a significant association between successful learning divisibility rules and the changes in frequency of task-related EEG.[66] This neurophysiological modulation may facilitate signal acquisition for SMR-BCI performance. Education is the repetition of learning for the development of a broad base of knowledge. Repetition of a motor imagery task improves SMR-BCI performance.[16] We propose that repetition of learning may facilitate the generation of optimal SMR patterns for the operation of an SMR-BCI.

Conclusions and Future Perspectives

SMR-BCI holds great potential for widespread application of both healthy and physically limited patients. The goals of our current review paper were (1) to compile established literature about the effects of internal variables on SMR-BCI performance, (2) to identify predictive biomarkers of BCI aptitude and (3) to identify limitations and propose further perspectives of "ecological" MI-BCI research.

This review article is intended to serve as an overview of studies that examine the effects of internal variables on SMR-BCI performance. We may conclude that attention, motivation and neurophysiological signals other than SMR share significantly positive relationships with BCI performance. Conversely, quality of life and mood do not have any clear association with SMR-BCI performance. A comprehensive literature review yields several main predictors of SMR-BCI literacy: simple reaction time, spectral and network properties of resting state activity, adaptive strategies and co-adaptive strategies. The identification of biomarkers of effective SMR-BCI control helps to identify prospective candidates for SMR-BCI. Additional biomarkers would provide a more selective and sensitive screening tool for potential SMR-BCI users. More research is needed to identify additional biomarkers. For more details, please reference **Table 1**.

Due to the limited availability of this emerging technology, sample size has been a recurring concern for SMR-BCI research. More subjects would allow for the discovery of relationships with greater significance, the introduction of healthy controls and further investigation of additional variables. We proposed next steps for the SMR-BCI research with respect to internal variables. More research is needed to describe the influence of gender and education.

Abbreviations

ALS - amyotrophic lateral sclerosis; BCIs – brain-computer interfaces; CRR – correct response rate, cVEP- code-modulated visual evoked potentials; EEG – electroencephalography, EMG – electromyography, ERD - event-related desynchronization, ERPs - event-related potentials; ITR - information transfer rate; MI – motor imagery, MIT – motor imagery task without feedback, MS- multiple sclerosis; QCM – questionnaire for current motivation, QoL – quality of life; SEIQoL-DW – schedule for the evaluation of individual QoL direct weighting, SMR – sensorimotor rhythm; VEP – visual evoked potential

Conflicts of Interest

Dr. Christoph Guger is the CEO and owner of g.tec, a company that sells neurotechnology on the international market.

Drs. Horowitz and Korostenskaja declare they have no conflicts of interest.

Dr. Horowitz is an employee of University of Central Florida/HCA Healthcare GME Consortium, an organization affiliated with the journal's publisher.

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