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# A Review of Performance Variations in SMR-based Brain-Computer Interfaces (BCIs)

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**Abstract**

The ability to operate a brain-computer interface (BCI) varies not only across subjects but also across time within each individual subject. In this article, we review recent progress in understanding the origins of such variations for BCIs based on the sensorimotor-rhythm (SMR). We propose a classification of studies according to four categories, and argue that an investigation of the neuro-physiological correlates of within-subject variations is likely to have a large impact on the design of future BCIs. We place a special emphasis on our own work on the neuro-physiological causes of performance variations, and argue that attentional networks in the gamma-range (> 40 Hz) are likely to play a critical role in this context. We conclude the review with a discussion of outstanding problems.

## 1 A brief history of BCI-research

From the early days of research on brain-computer interfaces (BCIs) until about a decade ago, subjects had to undergo intensive training in order to acquire the new skill of operating a BCI [1–7]. In the past ten years, machine-learning algorithms have shortened training procedures and enabled higher information transfer rates [8–12]. Even though machine-learning continues to make important contributions to the field, advances have somewhat slowed down: recent studies often report only minor enhancements in classification accuracy [13–15]. At the same time, variations in performance across subjects remain substantial. In a recent study based on a two-class sensorimotor-rhythm (SMR) BCI, 30 out of 80 healthy participants (37.5%) did not achieve a classification accuracy of or above 70%, which is considered as the lower limit for reliable communication [16]. While this constitutes an improvement of 11.2% relative to a large-scale study published in 2003 [17], in which 48.7% of subjects did not exceed 70% accuracy, a substantial percentage of users remains incapable of communicating by means of a SMR-BCI. Unfortunately, completely locked-in patients in late stages of amyotrophic lateral sclerosis (ALS), i.e., those subjects that stand to benefit most from BCI technology, appear to belong to this group of incapable subjects [18]. Inter-subject variations in performance have been reported to be less severe for P300-systems based on visual stimuli [19]. These results, however, may have been confounded by overt visual attention [20] - a skill not readily available to many patients in need of a BCI. Accordingly, the subsequent focus of this review is on SMR-based BCIs. Other experimental paradigms are briefly discussed in Section 4.

# 2 Performance variations in BCIs

The substantial variation in performance across subjects has triggered a new research direction that aims to identify variables associated with good and poor BCI performance. This in turn may lead to enhanced training strategies and novel ways to adapt machine-learning algorithms to different types of users. Studies on BCI performance variations can be classified according to (at least) four categories:

1. **Type of explanatory variables**

   Different types of variables may serve as the independent variable(s) in models used to explain variations in BCI performance. These range from psychological characteristics, such as the IQ score or level of depression, through neuroanatomic properties, e.g., as obtained by MRI scans, to neuro-physiological features such as resting-state $\alpha$-power. While each type of variable may provide interesting insights, their utility may differ. For instance, neuroanatomical features that are unlikely to undergo substantial changes over a subject's lifetime may be useful for predicting whether a subject is capable of operating a BCI. They are less likely to be useful, however, for assessing learning-related changes across multiple training sessions. Accordingly, studies should not only identify the types of variables under investigation, but also discuss their potential utility in BCI research. This issue is closely related to the second category.

2. **Correlates or causes of performance variations**

   Any type of variable found to correlate with BCI performance may, at least in theory, be used to predict whether a novel subject is likely to be able to operate a BCI. Only certain types of variables, however, are amenable to procedures, subsequently termed *interventions* [21], that transform poorly performing subjects into able BCI operators. For instance, it is conceivable that age correlates with BCI performance, with younger subjects performing better than an elderly (but otherwise matched) control group. It is difficult to conceive of an intervention, however, that alters the age of an individual subject. As such, this correlation would constitute an interesting insight, but would not give rise to novel strategies for enhancing performance in individual subjects. In contrast, a correlation between depression levels and performance could be interpreted as indicating that psychotherapy would influence a subject's ability to operate a BCI. The conceivability of such an intervention is not sufficient, however, to demonstrate its utility in BCI research. According to Reichenbach's principle, a correlation between two variables $x$ and $y$ can arise either because $x$ is a cause of $y$, $y$ is a cause of $x$, or both share a (possibly unobserved, i.e., latent) common cause $h$. In the present example, it is conceivable that both BCI performance and depression levels are affected by age. The ensuing spurious correlation between depression and performance could then lead to the erroneous belief that psychotherapy would influence BCI performance. In order to increase the probability that novel insights translate into actual benefits for BCI users, we consider it important to focus on variables that are likely to be actual causes, rather than mere correlates, of performance. We denote a variable as a cause of BCI performance if a) it is conceivable to construct a setup that experimentally sets the value of this variable, and b) if setting this variable to different values would result in statistically significant changes in performance. While ultimately only randomized controlled trials can establish such causal relations, the field of causal inference provides powerful tools that support the identification of causal relations from non-interventional data (cf. Section 3). Future studies should clearly indicate whether they aim to identify correlates or causes of BCI-performance.

3. **Inter- or intra-subject variations**

   Variations in performance may be studied on the inter- and intra-subject level. In the former case, each subject's BCI performance, in combination with one personal attribute, constitutes one observation pair. Observation pairs from multiple subjects may then be used to uncover potential correlations. This approach implicitly assumes that there exist invariant traits that determine a subject's capability to operate a BCI. In contrast, the intra-subject level focuses on changes in performance levels of individual subjects over time. In this case, multiple observations may consist of individual trials or separate recording sessions. As such, the actual time scale of such measures may vary from several seconds, as in the case of trial-to-trial variations, to multiple months, e.g., when investigating learning related differences across multiple sessions. Insights into inter- and intra-subject correlations may give rise to different strategies for enhancing BCI performance. For instance, inter-subject variations may be useful for predicting which subjects are likely to benefit from intensive training procedures. Intra-subject variations, on the other hand, might be used to monitor non-stationarities in recorded data and adapt machine-learning procedures accordingly.

4. **Healthy subjects or patient populations**

> Even though the potential benefit for patients often serves as a primary motivation for BCI research, most existing studies have been carried out with healthy subjects [22]. While these studies undoubtedly provide relevant insights, their conclusions may not transfer to patient populations. Diseases such as ALS have profound and system-wide effects that may eliminate or even reverse effects found in healthy populations. Furthermore, certain interventions may be feasible for healthy subjects, but unrealistic to carry out with patients in late stages of ALS. Such issues need to be openly discussed.

In the following, we review studies published by other groups on BCI performance variations, and discuss how they relate to the four categories described above. The presentation of our own work is deferred to Section 3.

To date, all types of variables listed under the first category have been considered as potential correlates of BCI performance. Hammer et al. have assessed correlations between online classification accuracy in a SMR-BCI and a variety of psychological tests, including measures of visuo-motor coordination, attention span, intelligence, and verbal- as well as non-verbal learning abilities [16]. They found that visuo-motor coordination skills and the ability to concentrate on a task both exhibited significant positive correlations with classification accuracy ($\rho = +0.42$ and $\rho = +0.50$, respectively). A link between concentration and BCI performance is consistent with previous reports that motivation, which may facilitate concentration, plays an important role in BCIs [23]. This has led to the suggestion that feedback in BCIs should be designed to minimize frustration [24,25]. Contrary to the case of psychological measures, very little is known about neuroanatomic correlates of good and poor BCI performance. One notable exception is the study by Varkuti et al., which indicates that the structural integrity of the corpus callosum differs between able and non-able subjects [26]. As white matter structures, such as the corpus callosum, are known to be affected by ALS, this may provide an explanation for the poor performance of these patients in SMR-based BCIs. More attention than to neuroanatomic features has been paid to neuro-physiological correlates of performance. Halder et al. have compared fMRI scans of well- and poorly performing BCI subjects during motor-imagery and motor-observation, and found that capable subjects exhibited larger activations in supplementary motor area (SMA) and right middle frontal gyrus [27]. This is consistent with the interpretation that altered activity in SMA, as reported in ALS patients [28], may adversely influence BCI-performance. Blankertz et al. have presented empirical evidence that the resting-state amplitude of the SMR is positively correlated with subsequent classification accuracy ($\rho = +0.53$) [29]. This result suggests that the ability to suppress the SMR by means of motor-imagery, which constitutes the basic principle of SMR-BCIs [4], is related to its resting-state amplitude. Furthermore, it indicates that mental strategies that are aimed at enhancing resting-state SMR-amplitude could result in improved BCI performance. While the nature of suitable mental strategies is at present unknown, it is reasonable to assume that they may be related to psychological correlates of performance as investigated by Hammer et al. [16].

It is interesting to note that most studies published to date, with the exception of Varkuti et al. [26], refrain from openly discussing the distinction between correlates and causes of performance. Nevertheless, some studies propose interventions to enhance performance, indicating that a causal relation is suspected. For instance, Blankertz et al. suggest to train subjects to increase their resting-state (or pre-trial) SMR-amplitude by neurofeedback [29]. As the SMR's amplitude is used to infer a subject's intention, it is reasonable to assume that there exists a genuine causal link between idling SMR-amplitude and BCI performance. Furthermore, a pre-training strategy could be realized for healthy subjects as well as patients in late stages of ALS. This appears more challenging for the results obtained by Hammer at al., who also suggest training strategies for enhancing the ability to focus attention and improving visuo-motor coordination [16]. While it is conceivable that a training programme in visuo-motor coordination might enhance BCI performance in healthy subjects, possibly via modulation of the SMR's resting-state amplitude, it appears non-trivial to design such a programme for subjects with no (or only residual) movement capabilities. In general, studies that reproduce the results reviewed here in patient populations are urgently needed, as only the study by Nijboer et al. is not based on healthy participants [23].

Somewhat surprisingly, none of the studies discussed above consider intra-subject variations. In the following section, we first argue that an investigation of the causes of trial-to-trial performance variations in individual subjects is likely to have a large impact on the design of future BCI-systems, and then review our recent progress in this domain.

## 3 Within-subject variations and the role of attentional networks

When investigating BCI performance across subjects, variables of interest are typically correlated with session-averaged classification accuracy. This implicitly assumes that a subject's skill in operating a BCI remains constant over the course of a recording session. Interestingly, this is not the case. Subjects exhibit large variations in performance over the course of individual sessions. Figure 1 displays trial-to-trial variations in performance of two subjects performing a left-/right hand motor-imagery task (adapted from [30]). Here, each cross represents one trial, recorded over the course of one experimental session lasting for 20 minutes. The y-axis denotes the *certainty* of the employed machine-learning algorithm in correctly classifying a trial. As such, large positive values indicate easy to classify trials, values with small absolute values represent uncertain trials, and negative values denote incorrect decisions (more precisely, the values on the y-axis represent the distance of the trial's features from the separating hyperplane, with positive/negative values indicating that the trial's features are on the correct/incorrect side [30]). While both subjects are able BCI performers,

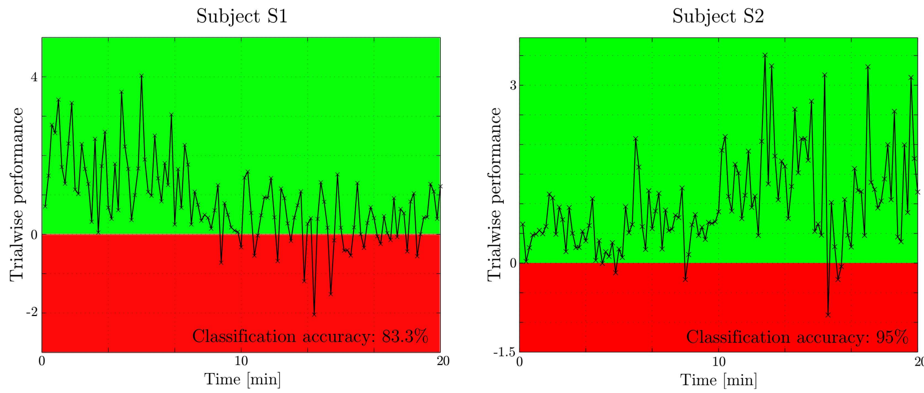


Figure 1: Trial-to-trial variations in performance of two subjects performing a left-/right hand motor-imagery task (adapted from [30]). See text for details.

with a session-average classification accuracy of 83.3% and 95%, respectively, there is a distinct temporal structure to each subject's performance. In the first few minutes of the recording session, subject S1 exhibits excellent performance, with no trials falling into the red region. After about six minutes, however, his performance starts to slowly decline, as seen by a downward trend of the decoding algorithm's certainty. For a few further minutes, however, his performance is sufficient to avoid incorrect classification. Only after about nine minutes into the session the first trial is incorrectly decoded. For the next seven minutes a large proportion of trials are not correctly classified. Only towards the end of the session a slight positive drift in performance is noticeable. Subject S2, on the other hand, shows a different temporal structure. While he already makes only few errors in the first few minutes of the session, his performance exhibits a further constant improvement. From about nine to 15 minutes into the session, not a single trial is misclassified. At 15 minutes, however, there is a sudden drop in performance, followed by a slow recovery extending all the way to the end of the session.

A subject's skill to operate a BCI may thus vary on a time-scale of a few minutes. Such changes are overlooked if only session-averaged classification accuracy is being investigated. But what are the causes of these variations? As for the case of inter-subject variations, this may be investigated on several levels. We have placed the focus of our work on the neuro-physiological level, which is based on the following considerations. Consider Figure 2, which depicts a thought experiment on the potential effect of a neuro-physiological cause of performance variations in a SMR-BCI. Assume we perform a study in which subjects are either at rest of perform motor-imagery of the right hand, and we record the electromagnetic field of the brain over primary motor cortex (MI). Depending on whether the subject is at rest or executes motor-imagery, we observe different distributions of bandpower in the $\mu$-range (10–14 Hz) (upper right corner). In this example, the optimal decision boundary for differentiating trials of rest- vs. trials of motor-imagery is given by the green line. Note that the overlap between the distributions, shown in dark gray, specifies the minimum Bayes error. Now assume that there exists a region in the brain, e.g., the prefrontal cortex (PFC), that modulates activity in MI. Further, assume that a change in PFC's activity induces a shift of the class-conditional distributions of $\mu$-power in MI to the right. In this case, which is depicted in the right lower corner of Figure 2, the original optimal decision boundary (shown in red) would be sub-optimal. Instead, the new optimal decision boundary would also have to be shifted to the right. If we knew that PFC modulates MI, we could monitor its activity and adapt our decoding procedure accordingly. This could give rise to new algorithms for adaptive BCIs [31–34]. It is also conceivable, however, that such modulatory effects do not induce a shift in the distributions of $\mu$-power, but rather alter their variance. This situation is depicted in Figure 3. Here, the optimal decision boundary for different activity levels of PFC remains identical. Strong activation of PFC, however, leads to a smaller overlap between the distributions of $\mu$-power at rest and during motor-imagery, resulting in a smaller minimum Bayes error (as indicated by the overlap of the two distributions shown in dark gray). In this thought experiment, the lower panel in Figure 3 thus represents a state-of-mind beneficial for operating a BCI, while the situation depicted in the upper panel results in lower performance. Knowledge about such a causal relation between PFC and MI could be exploited by several strategies. First, activity in PFC could be monitored and the initiation of a new trial could be delayed until a state-of-mind is observed that is likely to result in a correct decision of the BCI. This could increase information transfer rates and reduce frustration. Second, subjects could be presented with feedback on their current state of PFC activity, thereby teaching them how to induce a state-of-mind beneficial for operating a BCI. And finally, it is conceivable that such a causal link could be utilized by stimulating PFC, e.g., by transcranical direct current stimulation (TDCS), artificially inducing a state-of-mind in which subjects are capable operators of a BCI. To summarize, understanding the neuro-physiological causes of trial-to-trial performance variations would give rise to a variety of novel strategies for enhancing BCI performance in individual subjects.

In a series of recent studies, we have identified neural processes that qualify as potential causes of sensorimotor rhythms, thereby inducing changes in subjects' performance levels. In a study published in 2010, we presented empirical evidence that the amplitude of spatially distributed oscillations in the $\gamma$-range (55–85 Hz) correlates with a subject's capability to induce a lateralization of the SMR, as measured by the trial-wise performance metric shown in Figure 1 [35]. Interestingly, we found these $\gamma$-oscillations to only correlate with how well a subject modulated the SMR. They did not provide any information on its lateralization, i.e., whether subjects performed left- or right-hand motor-imagery. We analyzed these observations in the framework of Causal Bayes Nets [21, 36, 37], and argued that they provide evidence for a causal influence of the neural substrate of $\gamma$-range oscillations on the SMR. Based on this conclusion, we then hypothesized that the amplitude of $\gamma$-range oscillations would allow us to pre-

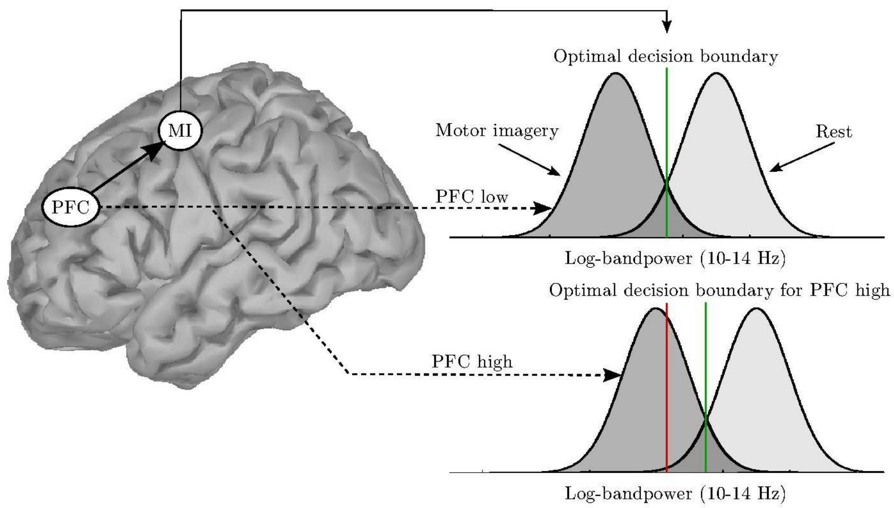


Figure 2: Thought experiment on the potential effect of causal relations between cortical areas on BCI-performance: Shift of distributions. See text for details.

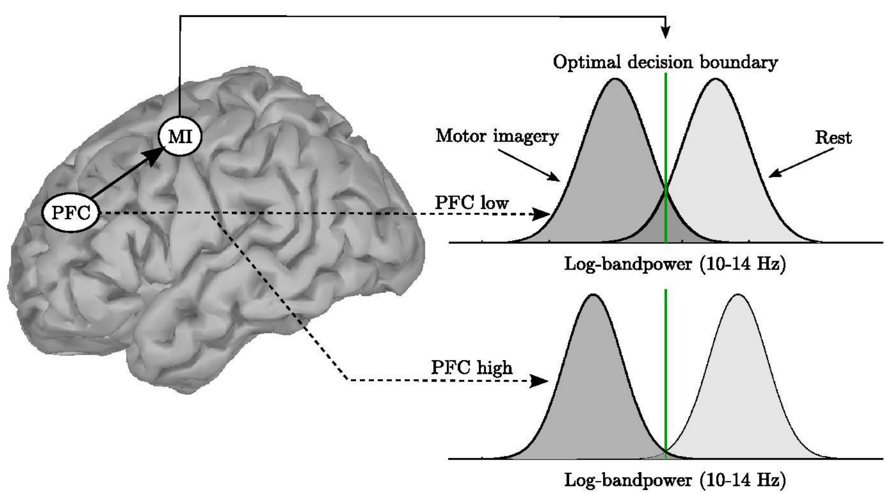


Figure 3: Thought experiment on the potential effect of causal relations between cortical areas on BCI-performance: Changes in variance of distributions. See text for details.

dict whether an upcoming trial is likely to be correctly decoded. We tested this hypothesis in a new group of subjects, and could present evidence that baseline $\gamma$-power (between 70–80 Hz) indeed predicts whether a subject is in a state-of-mind beneficial for operating a SMR-BCI [30]. To obtain a better insight into the nature of the involved processes, we carried out a source localization procedure. The obtained results indicate that BCI performance can be predicted from differences in $\gamma$-power between two fronto-parietal networks (cf. Figure 5 in [30]), which are believed to be involved in attentional processes [38]. This is in agreement with the observation that $\gamma$-range oscillations best predicted very slow changes in BCI performance, i.e., on a time-scale of multiple minutes, which is the dominant frequency range of attentional- and default mode networks [39]. In summary, these studies indicate that variations in activity between different attentional networks have an impact on a subject's capability to operate a SMR-BCI. The results discussed so far have been obtained with healthy subjects. Preliminary evidence indicates that similar relations may also be reproducible in subjects in late stages of ALS [40], but further evidence is required before any general conclusions may be drawn.

The next question, then, is how these insights may be used to enhance BCI-performance in individual subjects. Following the strategies outlined above, we first tested by how much we could increase session-average classification accuracy by rejecting trials according to their predicted probability of being correctly decoded [30]. This analysis indicated that, on a group level, classification accuracy could be enhanced by up to 15%. This, however, required rejecting 93.1% of trials. In any practical situation, a sensible trade-off between the two values would have to be chosen. It is important to note, however, that in this setup the prediction of performance was based on spontaneous variations in fronto-parietal activity. As all subjects had been instructed to focus attention on the task at hand, these natural variations may have been rather small relative to the extent that can be induced by volitional shifts of attention. Accordingly, we designed an experimental setup to test whether subjects could learn how to modulate fronto-parietal $\gamma$-power and use this skill to induce a state-of-mind beneficial for operating a BCI. As our previous results indicated $\gamma$-range oscillations to be an actual cause of the SMR [35], we hypothesized that modulation of fronto-parietal $\gamma$-power can be used to generate a strong idling SMR. In a pilot study, we trained three healthy subjects to modulate fronto-parietal $\gamma$-power by means of neurofeedback based on online beamforming [41]. Two of the three subjects displayed statistically significant control of $\gamma$-power after one and three training sessions, respectively. As hypothesized, volitional attenuation of fronto-parietal $\gamma$-power was accompanied by a statistically significant increase in $\mu$-power over sensorimotor cortex. These results indicate that subjects can learn how to generate a strong SMR by regulating fronto-parietal $\gamma$-power, thereby achieving a state-of-mind known to positively correlate with BCI-performance [29]. Before any general conclusions can be drawn, however, these results need to be reproduced in a larger population including subjects in late stages of ALS.

# 4 Discussion

In this article, we have reviewed recent progress on the correlates and causes of performance variations in SMR-based BCIs. While substantial progress has been made, this field of research is still in its infancy. In particular, a demonstration that the insights obtained to date transfer into enhanced classification accuracy in online BCIs remains outstanding. Considering the results obtained so far, it is quite likely that this will be achieved in the near future - probably by the SMR pre-training strategy proposed by Blankertz et al. [29] as well as by teaching subjects to attenuate fronto-parietal $\gamma$-power [41].

While such a demonstration would constitute an important advancement, many interesting problems remain. For instance, the results discussed in Section 3 only explain (a certain percentage of) performance variations on a time-scale of multiple minutes. From Figure 1 it is apparent, however, that subject performance further varies on a trial-to-trial basis, i.e., on a time-scale of roughly ten seconds. We are not aware of any studies investigating the neurophysiological origins of such fast variations. Also, there is at present insufficient evidence to conclude that ALS patients exhibit performance variations similar to those of healthy subjects, or that the same neural processes can be used to predict performance. Finally, it remains an open question how the neurophysiological correlates of performance, as discussed here, can be mapped back onto psychological states. For instance, mindfulness has been reported to enhance performance in SMR- as well as P300-based BCIs [42,43], and experienced meditators are more likely to be able to operate a SMR-BCI than healthy controls [44]. While it is reasonable to assume that these observations are related to the attentional networks discussed above, direct empirical evidence for such a relation is currently not available.

While we have placed the focus of this review on SMR-based BCIs, similar progress has been made in investigating the correlates of performance variations in P300-based systems. For instance, Mak et al. report that fronto-parietal $\theta$-power (4.5–8 Hz) is negatively correlated with inter-subject variations in a visual speller system [45]. As $\theta$- and $\gamma$-power often exhibit a positive correlation [46], the results of Mak et al. may be based on similar neural processes as those reported by us [30]. Further support for this hypothesis is lend by a recent study of Ahn et al., who found both $\theta$- and $\gamma$-power to predict inter-subject performance variations in SMR-based BCIs [47]. As such, it is not unlikely that the results discussed in this review are not specific to SMR-based BCIs, but may be linked to attentional networks that are relevant for a variety of experimental paradigms.

In the end, we hope that this new research focus will provide the necessary insights to construct BCIs that can be operated not only by healthy subjects but also by completely locked-in patients, no matter whether these systems will be based on the SMR, the P300, or utilize altogether different experimental paradigms [48, 49].

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