Abbreviated title: Neurofeedback success factors

Title: A systematic review of the psychological factors that influence neurofeedback learning outcomes

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**Abstract**

Real-time functional magnetic resonance imaging (fMRI)-based neurofeedback represents the latest applied behavioural neuroscience methodology developed to train participants in the self-regulation of brain regions or networks. However, as with previous biofeedback approaches which rely on electroencephalography (EEG) or related approaches such as brain-machine interface technology (BCI), individual success rates vary significantly, and some participants never learn to control their brain responses at all. Given that these approaches are often being developed for eventual use in a clinical setting (albeit there is also significant interest in using NF for neuro-enhancement in typical populations), this represents a significant hurdle which requires more research. Here we present the findings of a systematic review which focused on how psychological variables contribute to learning outcomes in fMRI-based neurofeedback. However, as this is a relatively new methodology, we also considered findings from EEG-based neurofeedback and BCI. 271 papers were found and screened through PsycINFO, psycARTICLES, Psychological and Behavioural Sciences Collection, ISI Web of Science and Medline and 21 were found to contribute towards the aim of this survey. Several main categories emerged: Attentional variables appear to be of importance to both performance and learning, motivational factors and mood have been implicated as moderate predictors of success, while personality factors have mixed findings. We conclude that future research will need to systematically manipulate psychological variables such as motivation or mood, and to define clear thresholds for a successful neurofeedback effect. Non-responders need to be targeted for interventions and tested with different neurofeedback setups to understand whether their non-response is specific or general. Also, there is a need for qualitative evidence to understand how psychological variables influence participants throughout their training. This will help us to understand the subtleties of psychological effects over time. This research will allow interventions to be developed for non-responders and better selection procedures in future to improve the efficacy of neurofeedback.

**Introduction**

Functional magnetic resonance imaging (fMRI)-based neurofeedback is a technique in the strong tradition of biofeedback approaches that utilises the latest developments of real-time data processing and pattern analysis to train participants in the self-modulation of neural networks (e.g. Sitaram et al., 2017). The training is based on the procedure whereby participants learn to control brain activity in specific brain regions or networks using real-time signals from their own brain (Johnston, Boehm, Healy, Goebel, & Linden, 2010; Scharnowski & Weiskopf, 2015; Sitaram et al., 2017).

We currently have a number of neurofeedback techniques at our disposal which utilise brain activity in different ways, three of which are considered in this review. The first involves fMRI, which works by detecting the concentration of oxygenated and deoxygenated haemoglobin in the neural vasculature. This is reflective of the metabolic demands of the underlying neural activation (Attwell & Iadecola, 2002). Real-time fMRI-based neurofeedback represents a particularly promising approach, due to its high spatial resolution and whole-brain coverages. It is also suitable for probing deep subcortical structures, which allows for the extraction of information from distributed activation patterns, and the mapping of functionally connected networks (Sorger, Reithler, Dahmen, & Goebel, 2012).

The second technique uses Electroencephalography (EEG), which measures the signals from extracellular field potentials in the brain using electrodes over the surface of the scalp. In real-time EEG, the signals are transformed into frequencies (e.g., delta (0–4 Hz), theta (4–7 Hz), alpha (8–12 Hz), beta (12–30 Hz) and gamma (>30 Hz) bands) before key features of the signals are extracted (Nicolas-Alonso & Gomez-Gil, 2012). The features extracted often include coherence (whether two signals are associated) or power spectral density (how the energy of a signal is distributed over time). These features can be used to interpret multivariate patterns in the signal called event-related potentials (ERP) and slow cortical potentials (SCP). These potentials respectively represent the shorter-term and longer-term changes in the EEG signal in response to an event or stimulus (Nicolas-Alonso & Gomez-Gil, 2012).

The final technique is brain-computer interface (BCI), where brain activity is linked up in direct communication with a device, such as a robotic arm. It is important to consider how BCI and neurofeedback relate to each other, as this can create confusion. BCI can be divided into two sub-categories as it can be utilised for both the purposes of neurofeedback; where brain activity is the focus, or for communication and control; as in the robotic arm example. In this sense, neurofeedback in general is a subdivision of BCI, as participants are mostly using their brains to communicate with a feedback device (such as a thermometer on a computer screen) but with the intention of learning to control brain activity rather than the device. Often in the literature, the expression "BCI" is exclusively used for the "communication and control" subcategory of BCI. However, the current review utilises examples of both subcategories. Understanding the BCI/neurofeedback relationship is particularly important in studies which have a communication and control BCI setup that also includes a neurofeedback training element. Typically, BCI utilises EEG (Jeunet, N’Kaoua, & Lotte, 2016) but theoretically could involve any imaging technique. EEG setups will often target P300 or event related potentials and sensorimotor rhythms (SMR), which are oscillations in the 8 to 30 Hz frequency range stemming from the sensorimotor cortex (Papanicolaou & Cheyne, 2017). Actual movement, as well as movement observation and imagination, induce a reduction in the amplitude of SMR, which is known as event-related desynchronization. SMR are often used because they are relatively easy to influence in an experimental setup (Nicolas-Alonso & Gomez-Gil, 2012).

One of the reasons why neurofeedback has been taken up with enthusiasm by the research community is that it responds to a huge clinical need for mechanism-driven therapies in neurology and psychiatry. Advances in neuroimaging and other neuroscience techniques have produced a wealth of information about the neural networks that can contribute to clinical disorders (Linden et al 2012) and thus inform treatment (Linden, 2006). Neurofeedback now offers the opportunity to harness this information to pinpoint and modify dysfunction and potential compensatory mechanisms in individual participants.

Despite being a new and emerging field, fMRI-based neurofeedback has already been used successfully to change brain responses in clinical populations, such as participants with schizophrenia (Ruiz et al., 2013) depression (Linden et al., 2012), obesity (Spetter et al., 2017), chronic pain (deCharms et al., 2005) and Parkinson’s (Subramanian et al., 2011). In the emotion processing domain, fMRI-based neurofeedback has proven particularly useful for up-regulating or down-regulating the brain regions involved in healthy adults’ emotional responses (Johnston et al., 2010; Paret et al., 2014, Zotev et al., 2011, Zotev, Phillips, Young, Drevets & Bodurka, 2013) and also in children and adolescents (Cohen Kadosh et al., 2016). The neural changes from fMRI-based neurofeedback are instantaneous but are also documented to last for up to 14 months in some cases (Megumi et al., 2015, deCharms et al.2005; Robineau et al., 2017). Critically, it has been shown that lasting effects of training not only result in the ability to influence one’s own brain activity, but are also related behavioural changes (Caria, Sitaram, & Birbaumer, 2012).

Despite these overall successes, it has been repeated found that not everyone who receives neurofeedback is able to influence their brain activity. These participants are often referred to in the neurofeedback literature as non-responders, non-performers or non-regulators and represent 30-50% of the population (Alkoby, Abu-Rmileh, Shriki, & Todder, 2017). Note that there is a similar issue in the BCI literature known as ‘BCI Illiteracy’ in which BCI is unsuccessful for 10-30% of participants (e.g. Vidaurre & Blankertz, 2010). Given the not negligible proportion of non-responders, there is a strong need to understand the inter-individual differences in neurofeedback performance.

It is the aim of this systematic review thus to explore this problem. Specifically, here we will assess how different psychological and cognitive factors relate to learning outcome in neurofeedback, and more importantly whether these could help to account for the differences between responders and non-responders. Factors implicated so far can be divided into psychological, learning dynamics or neurophysiological factors (Diaz Hernandez, Rieger, & Koenig, 2016). Variables can be further classified as being inter or intrapersonal (Grosse-Wentrup & Schölkopf, 2013), fluctuating states or stable traits (Jeunet, N’Kaoua, & Lotte, 2016) and explanatory or correlational variables (Grosse-Wentrup & Schölkopf, 2013). This review is focused on the psychological factors which relate to the learning outcome. This area is a priority as psychological variables are more likely to be open to intervention. Variables such as age offer insight, but it is difficult to improve the efficiency of neurofeedback based on this knowledge other than through selection processes (Grosse-Wentrup & Schölkopf, 2013). It is beyond the scope of this review to explore generic factors manipulated by the experimenter or other categories of predictor variables mentioned above (Paret, Goldway, Zicher, Hendler, & Cohen Kadosh, under review). For the purpose of the present study, relevant literature includes any study, experiment or review exploring psychological variables in relation to learning outcome. The psychological variables considered here will be all those implicated by the literature so far and include attentional, motivational, mood and personality factors (Alkoby et al., 2017). As the research body is only just starting to receive due attention and particularly for fMRI-based neurofeedback (Enriquez-Geppert et al., 2014), a wide range of populations and methodologies will be considered. That is, we will include both quantitative and qualitative research, using both EEG- and fMRI-based neurofeedback and also the BCI literature.

Both EEG and fMRI-based neurofeedback training have both been found to be successful and are sometimes used together (Keynan & Hendler, 2017; Zotev, Phillips, Yuan, Misaki, & Bodurka, 2014). Each approach has unique advantages and disadvantages. For example, fMRI can access deeper, subcortical areas due to the superior spatial resolution, which is in millimetres (e.g. Glover, 2011) as opposed to centimetres for EEG (e.g. Babiloni et al., 2001). EEG however has superior temporal resolution, accurate to milliseconds as opposed to seconds for fMRI (Weiskopf, 2012).

With the aim of this study satisfied, it is expected that there will be a clearer picture of where future research is required to understand the psychological differences between regulators and non-regulators. This can also begin to inform how psychological variables can potentially be addressed with tailored neurofeedback interventions to improve outcomes.

**Method**

A review of all published research up and until 2017 was completed using the online databases PsycINFO, psycARTICLES, Psychological and Behavioural Sciences Collection, ISI Web of Science and Medline. We note a descriptive systematic review approach was adopted here due to the significant variety of the methodologies and approaches used in the studies reviewed. Eight additional papers were identified through researchers in the field. Search terms were chosen to focus the literature search on real-time neurofeedback and BCI. The terms included were “real-time fMRI”, “real-time EEG”, “BCI”, “neurofeedback”, biofeedback”, “neurotherapy”, “bioneurofeedback” with both abbreviated and non-abbreviated terms applied. In addition, search terms were chosen to narrow the focus to psychological performance and learning variables, which were “factors”, “variable”, “predict”, “learning”, “response”, “mood”, “depression, “anxiety”, “attention”, “motivation”, “psychological”, “cognitive”, “personality” and “outcome” which were broadened with the asterisk function in search engines (e.g. “respon\*”). These two sets of search terms were combined with the “or” function on search engines.

Papers were screened in two phases; initially based on the relevance of their titles and abstracts allowing for some level of flexibility and then secondly the full body was assessed (See **Figure 1.** for a flow chart). However, we noted that often the studies did not include key findings about psychological variables in abstracts (as they were secondary findings) and so to counteract this, the method sections of all recent fMRI studies were examined by default. From this further examination, 33 articles were found that did not contribute to the current review due to a lack of consideration of psychological predictors. Abstracts were always examined as papers did not always included secondary findings in the title. Literature reviews and meta-analyses were always explored in full due to their utility in synthesising evidence. This approach is susceptible to bias in that the researcher may have naturally varied in their flexibility of exploring studies further based on titles and abstracts. Papers which cited neurofeedback or BCI (brain-computer interface) along with variables, predictors, factors, response or learning outcome were included. Papers which did not mention neurofeedback were excluded; for example, studies referring to static neuroimaging. Given the relative novelty of fMRI-based neurofeedback, all methodologies were considered.

**Figure 1:** Flowchart of the systematic review following the procedure set-out in *(Moher, Liberati, Tetzlaff, Altman, & PRISMA group, 2009)*

271 records identified through database searching

10 records identified through other sources

270 records after duplicates removed

270 abstracts screened

217 records excluded

54 full text articles assessed for eligibility

33 fMRI full text articles excluded as no inclusion/mention of psychological predictors

21 full text articles included in qualitative synthesis

**Results**

21 articles were found linking psychological factors to neurofeedback performance. In the following, factors are grouped into the categories of motivation, mood, attention, personality and more isolated research was grouped into the “other factors” category. The studies are indexed for convenience, as some studies explore multiple psychological variables. EEG studies are represented in **Table 1** and fMRI studies in **Table 2**, while both domains are organised according to the categories of variables in **Table 3**.

**Overview of Real-Time EEG Neurofeedback and BCI literature**

Attention: Of all the variables found in the literature,attention is likely to be the most important overarching psychological variable. Many studies investigating other variables, such as mood or motivation, attribute the differing performance of participants to the increased attention that comes from higher motivation or the consumption of attentional resources that arise from emotion. Both attention span and general ability to concentrate are implicated. For example, Daum and colleagues found participants with a greater attention span could achieve control over SCPs more successfully (Daum et al., 1993, **Table 1: 2**). Their study recruited 14 drug-refractory participants with epilepsy and tested them with cognitive tests from the Wechsler Scale of Intelligence (Wechsler, 1981). Attention was measured through performance on the digit span and block tapping test. The feedback task involved moving a rocket ship on a television screen forwards; which represented increased negativity. Success was based on the significance of SCP differentiation between baseline and active feedback trials. In line with these findings, Hammer and colleagues (Hammer et al., 2012, **Table 1: 6**) measured attention using the Cognitrone (Schuhfried, 2007); a performance measure of attention and ability to concentrate. This study focused on SMR to assess the influence of motivation on neurofeedback success. BCI performance for SMR control was measured through the percentage of correct responses of moving a cursor using imagery of the movement of hands and feet. The authors found that the ability to concentrate on the task accounted for 19% of the variance in performance. Note though that the runs took a considerable amount of time (up to 5 hours or more) and one might expect concentration to be of greater importance under such conditions.

Rather than measure attention specifically, other studies infer concentration from the neurofeedback trials themselves. Gruzelier and colleagues (Gruzelier, Hardman, Wild & Zaman, 1999, **Table 1: 5**) designed an EEG-based study to teach the reversal of neurological asymmetry in 25 participants with schizophrenia. They displayed the SCP negativity between hemispheres on the sensory-motor areas of the brain using an on-screen rocket. Participants were divided into good and average performers based on their neurofeedback ability. Average performers were not in fact slower learners, instead they dropped off in performance over time compared to good performers. This difference was most pronounced in the final block of three (each with 20 trials), leading the researchers to believe that the effects of fatigue on concentration made the difference between good and average performers, rather than learning. In addition, they found that depression and anxiety correlated negatively with performance. This was assessed using the Positive and Negative Symptom Scale (PANSS; Kay, Fiszbein & Opfer, 1987), a questionnaire which examines the symptoms of schizophrenia. Note that initial performance has also been linked to BCI success in SCP setups in a study by Neumann & Birbaumer (Neumann & Birbaumer, 2003, **Table 1: 13**). However, the authors attributed this finding to self-efficacy rather than attention as they had longer periods between training sessions (up to a month) and so participants had plenty of respite in between training blocks.

Motivation and Mood: Motivational factors appear to be among the most well-researched psychological variables in neurofeedback learning outcomes. Motivation can be defined in various ways, but many BCI studies utilise the QCMBCI, adapted from the Questionnaire for Current Motivation (Rheinberg, Vollmeyer, Burns, 2001), which has four subscales including “mastery confidence”, “interest”, “fear of incompetence” and “challenge”. For example, Nijboer and colleagues (Nijboer et al., 2008, **Table 1: 14**) used an SMR-BCI setup. Sixteen University students were instructed to visualise a movement that created their largest event-related desynchronization. The feedback given was either auditory by generating the correct sound (harps or bongos) or visual and involved moving a cursor across a screen to hit a target within a time frame. The authors were interested in how the accuracy of SMR manipulation was influenced by self-reported motivation. Nijboer and colleagues used the QCMBCI before each of the three training sessions. In visual feedback, they found mastery confidence correlated with accuracy (target hits), while fear of incompetence was associated with decreased accuracy. Additionally, they tracked those participants who scored worse over time and found that their mastery confidence was decreasing, and their fear of incompetence increasing, along with the deteriorating performance. However, this was not found for the auditory feedback condition. In fact, a relationship between improved accuracy and fear of incompetence was found in the auditory condition, suggesting that their anxiety lead to improved performance. The authors also found that improved mood prior to each training session correlated positively with improved SMR BCI performance (accuracy of cursor movements). They used a quality of life measure (Skalen zur Erfassung der Lebensqualität, SEL,; Averbeck et al., 1997) with ten Likert-scale questions relating to mood in the current situation. The authors noted that they could not derive a causal relationship of these factors due to the design of the study.

The authors followed up this study with similar study, which also included a condition looking at P300 control (Nijboer, Birbaumer & Kubler, 2010, **Table 1: 15**). The P300 is an ERP component that reflects attentional and working memory capacity (Kok, 2001). In this study, participants had to influence P300 to focus on characters in a letter matrix to copy a word, while the setup of the SMR BCI matched that of Nijboer et al. (2008). Seven participants with amyotrophic lateral sclerosis were organised into BCI training protocols for SMR BCI (1 participant), P300 BCI (3 participants) or both (3 participants). Within the P300 condition, a positive relationship between mastery confidence and letter selection accuracy was found in one participant whereas a negative relationship between fear of incompetence and accuracy was found in another. In the SMR group, challenge was positively correlated to accuracy in one participant. No other significant correlations were found including with mood; contradicting Nijboer et al., (2008). It is interesting that fear of incompetence related to outcome and anxiety on the measure of mood did not. It is possible that the quality of life measure lacks sensitivity. The study actually found significant correlations between the number of sessions and the psychological variables (e.g. many of the participants increased in motivational scores over time) and performance also increased in all SMR participants according to number of sessions. The correlations of psychological variables and performance may therefore be masked by the greater influence of the number of sessions.

These smaller studies depict how individual and variable the effects of motivation can be. An example of a larger study is that of Kleih and colleagues (Kleih, Nijboer, Halder & Kübler, 2010, **Table 1: 11**) who explored how self-reported motivation affected the ability of 33 psychology students to influence the P300 wave to spell words with a letter matrix. The authors found that self-reported motivation on a visual analogue scale (1-10) could predict 21.4% of the variance in P300 amplitude in sessions. They also found that a subscale of the QCMBCI called “challenge” significantly predicted spelling accuracy in single trials. This would suggest that participants who perceived the training as more of a challenge performed better. No other motivational scales predicted accuracy but note that accuracy in this study averaged at 99% and motivation in general was found to be very high. Therefore, for both accuracy and motivation (particularly on the “interest” and “mastery confidence” subscales of the QCMBCI) there were significant ceiling effects. Note that the primary aim of the study was to manipulate motivation with financial rewards for some groups of participants. To do this they offered either 25 or 50 eurocents for every letter spelled correctly. However, their rewards had no effect on self-reported motivation. According to Self-Determination Theory (Deci & Ryan, 1985), introducing extrinsic motivation from financial rewards would only serve to interfere with the high intrinsic motivation reported by participants in the study (Sarkheil et al., 2015), which could explain the problem. Kleih and colleagues suggested that the effect of motivation could be greater in studies with participants who were less motivated on average.

Perhaps, implicating the "interest” qualities of motivation, Leeb and colleagues (Leeb et al. 2007 **Table 1: 12**) used a virtual reality BCI task where participants had to navigate through a virtual apartment by increasing activity in motor regions through motor imagery (measured through EEG). Participants were previously trained with a cue-based feedback task where they would be presented with a smiley face on-screen if they responded correctly. All participants returned to this task following the virtual apartment task. Leeb et al., found that when participants started the virtual apartment task for the first time their performance (the number of errors they made) changed. That is, following the change to the virtual apartment, participants who were initially performing poorly on the cue-based task would perform better, while participants who were already performing well made more errors at first. Moreover, when participants returned to the cue-based task, all participants performed significantly worse. Participants reported that when they started the virtual apartment task they found it new and exciting. Leeb and colleagues attributed the findings to motivation. Participants who were not performing as well experienced new motivation for the new task and so their focus and performance improved. This was not the case with participants who performed well perhaps because they were already highly motivated and could only be distracted by the change. All of the participants found the cue-based task boring in comparison on return and were less motivated. Based on learning, one would expect the final session to elicit the least errors as participants were the most experienced, but this was not the case and performance was worse even than their first training session. This would therefore indicate that not only is motivation a key factor, but it is potent enough to override the learning effect. However, the results should be taken with caution as motivation was never measured, and fatigue may also have had an impact on performance as participants were tested for several hours.

While the QCMBCI appears to be a thorough assessment of motivation, another way of interpreting the concept of motivation comes from the idea of motivational incongruence (MI). MI is defined as the extent of mismatch between a person’s goals and motivation and what one truly perceives that they have achieved in their life (Diaz Hernandez et al., 2016). Diaz Hernandez and colleagues (Diaz Hernandez et al., 2016, **Table 1: 3**) conducted a study that involved learning to influence class D microstates. Class D microstates are EEG-based topographies of brain potentials, which have been linked to the positive symptoms of psychosis. They used the motivational incongruence scale (Holtforth & Grawe, 2003) to assess motivation in their participants. In this study, participants learned through auditory cue-based feedback (i.e. participants were instructed to increase the volume of a sound) and learning was measured both across different sessions and within individual sessions. They found that motivational incongruence accounted for 36% of the variance of learning (i.e. increase of microstate D contribution compared to baseline) between training sessions and 42% of the variance within a session. The authors concluded that motivational incongruence is linked to learning in neurofeedback. These findings link with the theory by Grawe (2004) that those with high motivational incongruence have internally conflicted processes in their goal directed behaviour (i.e. approaching goals versus avoiding them). This interferes with psychological functioning and effective interaction with the environment. One might argue that this could also relate to mood. For example, those whom are less satisfied with their goals may score higher on depression. The study only considered trait anxiety measure with the state version of the State-Trait Anxiety Inventory (STAI; Spielberger, 2010) with respect to mood and had no significant findings, though this may be due to anxiety being generally very low in the group they tested.

Other studies have found no link with motivation or even a negative relationship. Some authors of an earlier mentioned study (Kleih et al., 2010, **Table 1:11**) used the same setup as before to test P300 manipulation (Kleih and Kübler, 2013, **Table 1:10**) together with a customised motivational questionnaire to assess intrinsic versus extrinsic motivation for BCI. Participants were grouped into motivated and unmotivated groups, with motivated participants viewing an interesting presentation about BCI and potential benefits of its research, whereas the unmotivated group experienced a boring presentation. The presentation did not influence the motivation of groups according to scores on a visual analogue scale of motivation (measured before and after the presentations) but the groups did significantly differ in their motivational scores regardless, with the intrinsically motivated group possessing a greater mean score. The groups also significantly differed in the “interest” subscale of the QCMBCI prior to the presentations (this was not assessed post presentations). Kleih and Kübler also measured ability to concentrate with the d2 test (Brickenkamp, 2002) after the presentations, which measures both speed and accuracy of visual scanning. Test subjects must quickly cross out certain “d” symbols on a page while ignoring similar distractor stimuli (e.g. “p”). Strikingly, those in the motivated group scored significantly poorer on the attentional task, which they theorised could have been due to attentional resources being consumed during the presentations in more motivated people. In addition, there was no difference in the motivated and unmotivated groups according to P300 accuracy in BCI, which in this case may have been explained by the difference in attentional performance. In addition, the earlier mentioned study by Hammer and colleagues (Hammer et al., 2012, **Table 1: 6**) also found no significant link between motivation measured by the QCMBCI and SMR influence (shown through cursor movement) in a single session of imagining movements of hands. They suggested that the lack of findings may relate to the fact that their participants (a sample of 83 people mostly in higher education) were more homogenous than the general population in terms of motivation.

Enriquez-Geppert and colleagues (Enriquez-Geppert et al., 2014, **Table 1: 4**) explored the neurofeedback of frontal-midline theta (fm-theta) waves with EEG through an on-screen coloured square (with red suggesting an increase in fm-theta as opposed to blue). Fm-theta waves have been associated with improved task performance and enhanced cognitive processing (Mitchell, McNaughton & Flanagan, 2008). Two independent raters looked at the change in fm-theta frequency and rated participants as 1 to 5 on a Likert scale (1 was no response where 5 was strong response) and if scores of 1 and 2 were agreed upon, the participant was considered a non-responder. A quarter of the 31 participants did not respond to training according to this rating but this was not found to be linked to motivation, commitment or task difficulty; with these factors being self-reported according to a 7-point Likert scale. Instead, the authors suggested it was due to the strategy taken and mid-cingulate fissurisation interfering with fm-theta. It is also noteworthy that this study found that real or sham feedback did not affect the motivation of participants.

One final study in this area explored mood in relation to hemispheric negativity. Hardman and colleagues study (Hardman et al., 1997, **Table 1: 7**) involved on-screen feedback through a rocket ship to indicate negativity between frontal hemispheric areas. This time a subset of participants was instructed to imagine positive emotions to activate the left hemisphere and negative emotions to activate the right, while the other participants were given no strategy. There were no differences between groups and both were successful by the third trial in influencing negativity. Participants completed the Personality Syndrome Questionnaire (PSQ; Gruzelier & Kaiser, 1996), which has four subscales including “active”, “withdrawn”, “unreality” and “differential attentional processes inventory”. Through their observation of individual data, they found “withdrawal” to link with interhemispheric SCP control (Hardman et al., 1997, **Table 1: 7**). Specifically, those with higher withdrawal scores achieved greater rightward shifts in negativity. The withdrawal dimension includes elements such as social anxiety or being emotionally withdrawn. This suggests that pre-training emotional traits can predict the success of certain tasks within neurofeedback.

Personality and other factors: Overall there appears to currently be inconsistent support for personality as an influential variable. For example, in a study reviewed above, Diaz Hernandez et al. (2016, **Table 1: 3**) found no relationship with personality (along with “body awareness”) with the ability to influence microstates. These variables were assessed through the Five-Factor Personality Inventory (Borkenau and Ostendorf, 1993) and the Body Awareness Questionnaire (Shields et al., 1989) respectively. As reviewed above, Hammer and colleagues (Hammer et al., 2012, **Table 1: 6**) also found no personality factors from a measure of the “Big Five - Plus One” (Holocher-Ertl, Kubinger, & Menghin, 2003) that significantly predicted performance. The study by Kleih and Kübler (Kleih & Kubler, 2013, **Table 1: 10**) is the only study to date which explored the influence of empathy and found this to be negatively related to the P300 amplitudes achieved by participants. The authors wondered if empathy for end users of BCI measured with the Saarbrücker Personality Questionnaire (SPF; Paulus, 2009) would improve motivation and performance, and found the reverse to be true. It was speculated by the authors that empathy may increase emotional involvement with the study which interfered with the allocation of attentional resources.

In terms of other variables along with personality, BCI literature is relatively well researched for general predictors of training success and reviews such as Jeunet, N’Kaoua and Lottte (2017) show the diversity of potentially relevant variables. It is possible that some of the variables implicated are specific to the requirements of SMR BCI. For example, in an SMR BCI setup with 18 participants, Jeunet and colleagues (Jeunet et al., 2015, **Table 1: 8**) found that abstractness (relating to creativity) and mental rotation were related to SMR BCI success involving imagined movements. The imagination of movement may specifically demand spatial abilities and creative thought. Neurologically, high aptitude participants in SMR-BCI will recruit greater volumes and exhibit increased activation in supplementary motor areas (Halder et al., 2011). However, tension, learning style and the trait of self-reliance also related to BCI success. Tension is likely to closely relate to anxiety but learning style and self-reliance appear to be less researched and interesting findings. Similarly, an exploratory study by Kikkert (Kikkert, 2015, **Table 1:9**) into neurofeedback for the influence of EEG frequency bands found the potential influence of a wide array of variables. This included cognitive style, learning style, motivation, perceived session difficulty, the big five personality traits and mindfulness. The influence of these variables depended on whether the changes were phasic or tonic, or whether beta enhancement or theta inhibition was the goal. For example, locus of control was found to relate to greater beta increases in participants for phasic learning but had no significant relationship with other conditions.

Locus of control is the final recurring concept in the EEG and BCI literature. Burde and Blankertz (Burde & Blankertz, 2006, **Table 1: 1**) used EEG to measure activity in motor areas and asked 12 participants to imagine movements in the hands and feet within a single session. Participants were asked to increase activity in motor areas through this imagery to move a cursor to the edge of a screen. The number of successful screen hits a participant had correlated with their scores on a scale of loci of control over technology (KUT; Beier, 2004). This study was followed by a study by Witte and colleagues (Witte et al., 2013, **Table 1: 16**) who also used scores from the KUT as an independent variable. However, they tapped directly into SMR power and fed this back with the relative size of on-screen bars. They found that participants who held stronger beliefs that they could influence technology were actually less able to up-regulate SMR. The researchers suggested that in this particular study, relaxation is an important pre-condition for learning to synchronise SMR. Therefore, control confidence negatively affected this ability as it recruits non-SMR related neural resources. Based on the findings of other studies (e.g. Nijboer et al. 2008, **Table 1: 14**) it is possible that fear of incompetence may play role as well if poor performance may lead to greater negative emotions in those with a greater locus of control and their resulting higher expectations.

**Overview of Real-Time fMRI Neurofeedback Literature**

In fMRI-based neurofeedback research, one study used the advantages of fMRI to explore the influence of attentional networks and give further understanding of the importance of attention in neurofeedback. Chiew and colleagues trained participants to influence BOLD activity in motor areas of the brain during imagined motor movements. In contrast to other studies, less than an hour was required for participants to finish the runs in this experiment. They found that activity in task-related networks could account for 65.6% of variance in right handed people and 17.6% in left handed fMRI performance (Chiew, Laconte, & Graham, 2012, **Table 2: 1**). This task-positive network has been attributed to attention and engagement in the neurofeedback task and includes the frontal eye fields (premotor), insula and dorsolateral prefrontal areas. Activity in this network was associated with performance even in the first training session, which would indicate that initially the neurofeedback success is not a learning effect but an attentional one.

In the fMRI research into emotional regulation, there has been an interest in the trait of susceptibility to emotion and coping strategies as well as straightforward mood states. Marxen and colleagues (Marxen et al., 2016, **Table 2: 3**) utilised fMRI-based neurofeedback to teach 35 healthy participants to influence BOLD signal from the bilateral amygdala with the aim of eventually removing feedback for more long-term learning. Feedback was visual and involved moving dots on a screen towards a target. Successful learning was defined as a demonstration of significantly different BOLD signals in the amygdala between up-regulation attempts and downregulation. They found that self-rated susceptibility to anger (from the Emotional Contagion Scale; Doherty, 1997) was negatively correlated with emotional regulation capacity following fMRI-based neurofeedback. This was the only effect they found, and state anxiety and depression measured through the STAI (Kendall et al., 1976) and Beck Depression Inventory (Beck et al., 1996), were not found to have a statistically significant relationship with the regulation during training. However, in terms of personality, they found that agreeableness as measure through the NEO-Five Factor Inventory (Costa and Mccrae, 1992) was negatively correlated with regulation capacity in their post training runs where feedback was not given to test the learning of participants. This was the only personality factor they found to link at all with regulation. The authors did not offer an explanation, but it could be suggested that those participants that are more agreeable find it more difficult to manage emotions, which is an interesting finding and somewhat contrary to what might be expected. It is possible that those who are agreeable had a desire to please the experimenters which was consuming attentional resources, such as through fear of incompetence. Finally, the authors found that participants ratings of how well they manage emotion using the Emotional Regulation Scale (Gross & John, 2003) correlated with regulation capacity post fMRI-based neurofeedback training; though only when feedback was present.

Another similar fMRI study by Zotev and colleagues (Zotev et al., 2011, **Table 2: 5**) investigated amygdala regulation through the use of positive autobiographical memories with 28 healthy volunteers. One specific aim was to increase activation of the left amygdala with emotionally evaluating stimuli. This study included both an experimental and sham feedback control condition and participants were matched on variables such as education. They found that participants who rated themselves as more susceptible to anger exhibited less BOLD activation in the left amygdala during training. It is interesting that neurofeedback would be less successful for those with high levels of susceptibility in the two studies above. Previous research has highlighted the important role of the insula in the regulation of emotion (e.g. Ruiz et al., 2013), and it may therefore be worth to routinely examine insula activity in those who are susceptible to emotion. Susceptibility may be associated with traits such as empathy which are considered a positive social trait. However, it may have a downside in that some people with high susceptibility or empathy may experience vicarious emotion that is difficult for them to regulate. It is also noteworthy that both of the above studies contradicted each other in their findings about the ability to label emotions. That is, Marxen and colleagues (Marxen et al., 2016, **Table 2: 3**) found no correlation of amygdala regulation with scores on the “difficulty identifying feelings” scale (Toronto Alexithymia Scale; Bagby et al., 1986), whereas Zotev and colleagues found with the same scale that those with lower scores for difficulty identifying feelings, achieved superior amygdala regulation from training (Zotev et al. 2011 **Table 2: 5**). One possible explanation is that this relates to strategies during training. In the study by Zotev and colleagues, participants were asked to recall positive memories to respond to feedback, whereas no such strategy was suggested by Marxen and colleagues. A strategy requiring positive memory recall specifically may require accurate labelling of the emotions tied to memories, whereas participants in the Marxen and colleagues could use any strategy and so would not be as limited by the labelling ability.

Interestingly, emotional difficulties in themselves do not always appear to be a hindrance for neurofeedback. For example, Nicholson and colleagues used fMRI-based neurofeedback to explore down-regulation of amygdala regulation in 10 participants with post-traumatic stress disorder (PTSD) following exposure to trauma trigger words. Participants completed three training sessions and a transfer run without feedback given. Symptom severity was measured with the Clinically Administered PTSD Scale (Blake et al., 1995). In sessions one and three, they found that participants with more severe post-traumatic stress disorder symptoms could achieve greater down-regulation of amygdala activity (Nicholson et al., 2017, Table 2: 4). It is possible then, that there is more to gain when there are already neurological emotional regulation deficits.

Finally, there is also some evidence that specific pre-existing coping strategies that people have can predict their success in neurofeedback training. For example, in an fMRI-based neurofeedback study on coping with pain through heat stimulation, Emmert and colleagues (Emmert et al., 2017, **Table 2: 2**) assessed self-reported scores of the frequency of active pain coping strategies measured with the Coping Strategies Questionnaire (Rosenstiel & Keefe, 1983). They found that the use of active pain coping strategies predicted the success of participants at regulating pain-sensitive regions of the brain.

**Summary of Findings Across the Literature**

To conclude, the ability to concentrate and sustain attention is likely to be a key predictor of success in neurofeedback. Attentional abilities should be established prior to training. It would be helpful research to establish tailored programmes for people with attentional difficulties; for example, with shorter sessions or more simple training setups and tasks with minimal distractors. However, other psychological variables such as motivation are likely to also influence attention. As such a profile of each participant should be established before considering how to maximise the efficiency of their training.

For neurofeedback to be maximally effective, the motivation of participants needs to be taken into account. To do this, monitoring of motivational changes is indispensable. It is recommended that more comprehensive scales such as the QCMBCI are utilised rather than generic Likert scales as motivation consists of various factors which may differ in the individual. For example, participants may be motivated in terms of interest but have little mastery confidence. Generally, participant motivation in this field of research is high but poorer performances can increase fear of incompetence and reduce mastery confidence which can lead to disengagement with the task and a potential label of “non-responder” for individuals over time. Should this be found, interventions for decreased motivation could include extrinsic rewards (e.g. financial), discussion of alternative strategies or positive encouragement for performance. There have been successful attempts in the past to manipulate emotion with monetary reward (e.g. Shibata et al., 2011; Contese et al., 2016) and detailed analysis of the effect of such manipulation (e.g. Sepulveda et al., 2016), which is promising with regards to the development of tailored interventions for non-responders with low motivation. It can be difficult to manipulate motivation in neurofeedback and BCI research because participants tend to be so intrinsically motivated initially that any additional motivating methods; such as extrinsic rewards or interesting presentations, only serve to interfere. Therefore, to address this, researchers may consider manipulating how interesting the neurofeedback task is in itself for different groups, as done in Leeb et al. (2007, Table **1: 12**). Also, while the ethics would need careful consideration, in some cases there may be the possibility of manipulating sham-feedback to influence variables such as mastery confidence. Otherwise, high and low motivated groups should be established from participants prior to training and compared in neurofeedback success to evidence the predictive utility of this variable.

With the inconsistency of the results of mood research, it is possible that mood affects performance in a task-specific way. For example, those with higher depression or anxiety scores may be able to generate right-ward shifts in hemispheric activity more readily compared to left-ward shifts. This area requires further investigation and it is recommended that researchers consider using robust measures of current mood and anxiety rather than Likert scales (unless used in combination) to ensure adequate reliability and validity. It seems likely that anxiety can impair training success across a range of neurofeedback set-ups and it should therefore be monitored regularly through training. Interventions could include discussions of fears and worries, offering reassurance and anxiety management techniques such as relaxed breathing or progressive muscle relaxation (Roth & Pilling, 2007). Susceptibility to emotion also appears significant to emotional regulation neurofeedback studies and so should not be overlooked in this branch of neurofeedback research.

Personality factors such as the “big five” have yet to show consistent evidence of their effect on neurofeedback. Cases where the factors have been found to be associated with performance are probably better explained in terms of the consumption of attentional resources, anxiety and motivational factors. Those who are more agreeable and wish to please the experimenters or those who are overconfident, may consume more resources considering whether their performance is satisfactory than attending to a task. However, it is well worth considering other factors which may be specific to the research being carried out. This is exemplified by the significance of individual pain management strategies in a neurofeedback study to do with coping with pain (Emmert et al., 2017, **Table 2: 2**).

Finally, it is worth noting that these variables may relate differently to the neurofeedback success, depending on whether a pure feedback learning through operant conditioning was used, or a specific mental strategy. For example, those who are struggling with pure feedback may gain an improvement in motivation, mood and attention by being given new strategies to try.

**Discussion**

As a result of significant advances in fMRI-based neurofeedback technologies, the field of neurofeedback has experienced a surge in research activity and publications (Sulzer et al., 2013). However, it has also been shown that not all participants benefit from the training and it appears that comparative to BCI and EEG literature, there are fewer studies which explore the predictors of success in fMRI-based neurofeedback. Here we conducted a literature review to explore the psychological variables that are implicated as being influential in neurofeedback learning outcomes. Specifically, we looked at attention, motivation, mood and personality factors along with any other evidence for unique factors such as “body awareness”. However, our findings also have implications for the BCI literature as there appears to be significant crossovers in methodology and findings between neurofeedback and BCI. We would therefore recommend that those conducting BCI research should also consider the psychological variables implicated in the current review to aid understanding and interventions for the issue of BCI illiteracy. Overall, the research that has been conducted suggests that there are moderate psychological influences. In addition, the influence of these variables is complex. For example, it is not simply a case that better mood relates to better learning. Fear of incompetence can lead to improved performance in some cases while it is detrimental in others (Nijboer et al., 2008). Attention was found to have the most consistent positive influence on learning and performance in neurofeedback tasks across fMRI and EEG. All four studies concerning this variable found such a result.

Out of the eight studies that looked at motivational factors, five found at least some influence of motivational factors on performance or learning. For the most part, it seems motivational factors can increase the focus on the task. In this way motivation probably relates at least in part to the distribution of attentional resources. Other than general Likert ratings of motivation, more specific variables implicated to improve performance include interest in the task, confidence in mastering the task and the challenge perceived in the task (Nijboer et al., 2008; Nijboer, Birbaumer & Kubler, 2010; Kleih et al., 2010). On the other hand, fear of being incompetent in a study and incongruence in goal-seeking behaviour are predictive of poorer performance and learning (Nijboer, Birbaumer & Kubler, 2010; Diaz Hernandez, Rieger & Koenig, 2016). Motivation generally is reported to be high by people taking part in neurofeedback studies, possibly due to how participants are recruited (often through self-selection) and the because of the treatment potential of certain conditions.

Regarding mood and emotional factors, anxiety and depression are implicated to have a negative influence on performance (Gruzelier, Hardman, Wild & Zaman, 1999; Hardman et al. 1997; Nijboer et al., 2010). The susceptibility people have to the emotion of others also appears to play a part in emotional regulation learning. For example, susceptibility to anger has been found to link to impaired emotional regulation in two fMRI-based neurofeedback studies (Marxen et al., 2016; Zotev et al., 2007). Moreover, under specific circumstances, the ability to label emotions may be important in emotional regulation learning (Marxen et al., 2016).

For personality and other variables there were several other possible influential variables implicated. Personality is mostly found to have inconsistent influence, with few significant findings found. However, agreeableness has been found to negatively relate to emotional regulation learning with fMRI-based neurofeedback (Marxen et al. 2016). Two studies found locus of control to be significant but in contradictory ways; one finding locus of control over technology to improve performance (Burde &Blankertz, 2006) and the other found it made it made performance worse (Witte et al., 2013). Empathy was also found in one study to negatively influence performance (Kleih & Kubler, 2013). Also coping strategies for pain predicted success in reducing activity in pain sensitive regions (Emmert et al., 2017).

The variety in variables targeted for learning or performance in neurofeedback and BCI research is extensive. Even within the current survey are studies looking at hemispheric asymmetry, microstates, SMR, BOLD levels or P300 amplitude. In addition, different areas or circuits of the brain are often utilised as targets for certain activity to be modified and methodologies and training protocols vary significantly. The variety of research carried out does offer a degree of cross-methodological validity. It is certainly ever more convincing that people are able to modify a remarkable variety of neurological activity through training and computer interfacing.

While neurofeedback is promising, the issue with non-responders needs to be addressed. It would be beneficial to understand this group of people better. There is first a question as to whether barriers to responding can be overcome or whether better selection of participants is required. It has also not yet been tested whether non-responding participants in one study would also not respond to training in another. In other words, there is a question as to whether non-responders are generally unable to modify brain activity or whether they have specific psychological characteristics which prevent them learning to modify one area of the brain or particular brain waves. One might certainly expect differences; for example, mood may be a more important variable in studies looking to modify activity in areas of the brain associated with emotion.

The research into psychological variables is particularly limited. Up until now, neurofeedback studies have rarely explored psychological variables or non-responders generally as a primary aim. That is, most research does not separate out non-responders as a group and explore in detail how their psychological variables differ, what their difficulties non-responders face and what their experience of the training is like in comparison to those who are successful (e.g. what strategies are they using or how is their motivation changing over time). It also seems to be unclear as to what the consensus is as to which participants are considered to be “non-responders” and for example, what the threshold level of successful response is (Emmert et al., 2016). Some BCI studies set a 70% accuracy threshold to differentiate successful and non-successful BCI (Alkoby et al., 2017). Alternatively, studies have defined success as the achievement of significant differences in responses between two conditions, such as differences in BOLD signals between up and down regulation conditions (e.g. Marxen et al., 2016) or differences in P300 amplitude between groups of participants (Kleih et al., 2010). Also, Gruzelier and colleagues (1999) used two independent raters to judge average from good performers of hemispheric shifts in negativity, with the aid of graphs. There are therefore a variety of methods for defining success which will also vary based on the methodology of the study.

Psychological factors in particular may affect training but also be affected by training. This is important because the research which has explored this area often relies on correlation and researchers have yet to manipulate these variables successfully prior to training sessions. The design of studies needs to allow for prediction of success for psychological variables to be useful for training selection. The complexity of the effects of psychological variables also needs to be better understood. Qualitative evidence from interviews in one of the studies has captured interesting nuances in training performance specifically in relation to motivation with individuals along their course of training (Nijboer et al., 2010). Such work highlights that research into motivation should take into account a potential triangular relationship between mastery confidence, fear of incompetence and challenge and how this changes through a course of neurofeedback. Further research is now needed to explore such complexities further and also in relation to other implicated variables, such as mood or attention. It is not unreasonable to expect that all of the psychological variables mentioned in this review might influence each other and there is currently less focus on the individual change over training blocks and how this may relate to psychology. Rather it is more focused on correlations between psychological variables and performance within training sessions. As the psychological variables seem inconsistent through the research, it would suggest that more detailed exploration of individual differences in how psychological variables affect the benefits of training are required over the course of training to understand the subtleties involved. These variables can fluctuate within seconds and so research should target both wider population effects and also more detailed research with individuals.

To conclude, in the future, high quality research is necessary to allow conclusions to be drawn confidently regarding psychological factors. This means that measures used to assess motivation, mood, and so on should have good reliability and validity and be sensitive to pick up the nuances of such variables. There needs to be recognition that psychological variables such as mood and motivation will vary over time and so need to be monitored throughout training. These variables also need to become more of a focus of manipulation; for example, by comparing groups of participants who score high and low on such variables. Researchers need to consider and distinguish between the two success outcomes of performance and learning during training and the relation of psychological variables to both. Finally, researchers should consider trialling interventions to reduce the effect of inhibitory psychological variables on neurofeedback success to increase the efficiency of this promising technique.

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*1.Table to Show EEG studies Implicating Psychological Variables in Neurofeedback performance*

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| **Results Section Index** | **Researchers** | **N** | **Relevant Independent Variable(s)** | **Dependent Variable(s)** | **Findings** |
| 1. | Burde & Blankertz, (2006) | 12 Participants | Locus of Control for technology | Motor region activity | Locus of control led to  greater accuracy |
| 2. | Daum et al. (1993) | 14 epilepsy patients | Attention span | SCP potentials learning | Performance improved in those with higher attention span |
| 3. | Diaz Hernandez, Rieger and Koenig (2016) | 20 healthy participants | Motivational incongruence, Life satisfaction, Body awareness Personality, trait anxiety | Self-regulation of EEG microstates | Negative correlation between Motivational incongruence and EEG microstate increase |
| 4. | Enriquez-Geppert et al. (2014) | 31 healthy participants – money reward | Self-reported motivation, commitment and difficulty | SMR Influence | No link - greater perceived difficulty in genuine group |
| 5. | Gruzelier et al. (1999) | 25 Schizophrenic patients | Anxiety, depression, psychosis | Asymmetry reversal | Anxiety and depression linked, positive symptoms of psychosis not. |
| 6. | Hammer, et al. (2012) | 80 Participants | Motivation, Degree of concentration | SMR Influence | Degree of concentration was a significant predictor |
| 7. | Hardman et al. (1997) | 16 healthy participants | Withdrawal (loneliness, lack of friends, social anxiety, emotional withdrawal) | Cortical asymmetry | More asymmetry in right hemisphere – less successful |
| 8. | Jeunet et al. (2015) | 18 Participants | Mental rotation, tension, self-reliance, learning style and abstractness | SMR BCI success | Mental rotation, self-reliance, abstractness positively correlate with BCI performance. Tension negatively related. |
| 9. | Kikkert (2015) | 34 students | Cognitive style, learning style, motivation, perceived session difficulty, the big five personality traits and mindfulness | Beta enhancement and Theta inhibition | Beta enhancement correlated with learning style, cognitive style, and locus of control. Theta inhibition correlated with factors such as mindfulness and reward sensitivity. |
| 10. | Kleih and Kubler (2013) | 21 Healthy Students | Motivation and Empathy | BCI performance and P300 | No link between motivated and unmotivated group and performance. Empathy did have a moderate effect |
| 11. | Kleih et al. 2010 | 33 psychology students | Incentive financial | Mood, motivation and P300 amplitude | Motivation predicted P300 amplitude. Motivation unrelated to money reward. |
| 12. | Leeb et al. (2007) | 10 paid volunteers | Motivation | BCI performance | Positive correlation between variables |
| 13. | Neumann & Birbaumer (2003) | Five severely paralysed patients | Initial BCI Performance | Final BCI performance | Initial Performance relates to continued success. |
| 14. | Nijboer et al. (2008) | 16 healthy volunteers | Mood and Motivation | BCI performance | Mood and motivation predicted performance |
| 15. | Nijboer, Birbaumer and Kubler (2010) | 6 adults with ALS | Psychological Well-being (Quality of life, depression, mood, motivation) | BCI performance | Challenge and mastery confidence related to BCI performance. Incompetence fear negatively related. Some participants did not relate. Mood unrelated |
| 16. | Witte et al. (2013) | 20 healthy participants | Locus of control | Sensori-motor rhythm up-regulation | Locus of control negatively correlated with performance |

*2. Table to Show fMRI studies Implicating Psychological Variables in Neurofeedback*

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| **Results Section Index** | **Researchers** | **N** | **Relevant Independent Variable(s)** | **Dependent Variable(s)** | **Findings** |
| 1. | Chiew, Laconte & Graham (2012) | 13 Participants | BOLD signal for task related networks (attention) | BOLD signal in motor areas | Neurofeedback success is attentional rather than a learning effect |
| 2. | Emmert et al., (2017) | 28 Healthy Participants | Self-reported Pain coping ability | Pain sensitive region regulation | Active coping strategies predicted neurofeedback success |
| 3. | Marxen et al. (2016) | 35 Healthy participants | Susceptibility to anger | Amygdala regulation | Positive correlation between variables |
| 4. | Nicholson et al. (2017) | 10 PTSD patients | Symptom Severity | Amygdala regulation | Greater symptom severity lead to greater down-regulation |
| 5. | Zotev et al. (2011) | 28 Volunteers | Identifying feelings, Susceptibility to anger | Amygdala regulation | Difficulty identifying emotions and susceptibility to anger both negatively correlated to amygdala regulation |

*3. Table to Show fMRI-based Neurofeedback and BCI studies Organised by Psychological Variables and their Categories*

|  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
| Psychological Variables | Study/Measure | Dependent Variable | Categories of Variables | | | | | |
|  |  |  | State | Trait | Correlational | Explanatory/Predictive | Interpersonal | Intrapersonal |
| Attention | Daum et al. (1993: Table 1:2); WAIS-R – Digit span, block tapping | SCP-BCI Performance |  | ✓ |  | ✓ | ✓ |  |
| Chiew, Laconte & Graham (2012; Table 2:1); BOLD activity in task related networks | fMRI-based neurofeedback – Motor areas | ✓ |  |  | ✓ | ✓ | ✓ |
| Gruzelier et al. (1993; Table 1:5); Inferred from training fatigue | SCP-BCI Performance | ✓ |  |  | ✓ | ✓ | ✓ |
| Hammer et al., (2012; Table 1:6); Cognitrone | SMR-BCI performance |  | ✓ |  | ✓ | ✓ |  |
| Motivation | Diaz Hernandez et al., (2016; Table 1:3). Motivational Incongruence Scale | Class D microstates – BCI Performance |  | ✓ |  | ✓ | ✓ | ✓ |
| Enriquez-Geppert et al., (2014; Table 1:4) 7-Point Likert Scale | Fm-theta – BCI Performance | ✓ |  | ✓ |  | ✓ | ✓ |
| Hammer et al., (2012; Table 1:6), QCMBCI | SMR-BCI performance | ✓ |  | ✓ |  | ✓ |  |
| Kleih & Kubler (2013; Table 1:10); QCMBCI, Customised intrinsic vs extrinsic motivation questionnaire, Visual Analogue Scale | P300 – BCI Performance |  | ✓ | ✓ |  | ✓ | ✓ |
| Kleih et al., (2010; Table 1:11); Visual Analogue Scale from 1-10, QCMBCI | P300 – BCI Performance | ✓ |  |  | ✓ | ✓ | ✓ |
| Leeb et al., (2007; Table 1:12); Inferred from novelty of task | Motor Imagery- BCI Performance | ✓ |  | ✓ |  | ✓ | ✓ |
| Nijboer et al., (2008; Table 1:14) | SMR-BCI performance | ✓ |  | ✓ |  | ✓ | ✓ |
| Nijboer, Birbaumer & Kubler (2010; Table 1:15) | P300 and SMR-BCI performance | ✓ |  | ✓ |  | ✓ | ✓ |
| Mood | Diaz Hernandez et al., (2016; Table 1:3) STAI – state version | Class D microstates – BCI Performance | ✓ |  | ✓ |  | ✓ |  |
| Gruzelier et al. (1993; Table 1:5); PANSS | SCP-BCI Performance |  | ✓ | ✓ |  | ✓ |  |
| Hardman et al. (1997; Table 1:7); Personality Syndrome Questionnaire | Hemispheric Negativity – BCI Performance |  | ✓ | ✓ |  | ✓ | ✓ |
| Marxen et al., (2016; Table 2:3); State-trait Anxiety Inventory and Beck Depression Inventory | fMRI-based neurofeedback, emotional regulation | ✓ | ✓ | ✓ |  | ✓ |  |
| Nijboer et al., (2008; Table 1:14) | SMR-BCI performance | ✓ |  | ✓ |  | ✓ | ✓ |
| Nijboer, Birbaumer & Kubler (2010; Table 1:15) | P300 and SMR-BCI performance | ✓ |  | ✓ |  | ✓ | ✓ |
| Personality | Diaz Hernandez et al., (2016; Table 1:3); Five-Factor Personality Inventory | Class D microstates – BCI Performance |  | ✓ | ✓ |  | ✓ |  |
| Hammer et al., (2012; Table 1:6); Big Five Plus One | SMR-BCI performance |  | ✓ | ✓ |  | ✓ |  |
| Marxen et al., (2016; Table 2:3) NEO-Five-Factor Inventory | fMRI-based neurofeedback, emotional regulation |  | ✓ | ✓ |  | ✓ |  |
| Other Psychological Variables | | | | | | | | |
| Empathy | Kleih & Kubler (2013; Table 1:10) SPF | P300 – BCI Performance |  | ✓ | ✓ |  | ✓ | ✓ |
| Initial BCI performance | Neumann & Birbaumer (2003; Table 1:13), in situ performance | SCP-BCI Performance |  |  | ✓ |  | ✓ | ✓ |
| Locus of Control | Burde & Blankertz (2006; Table 1:1); KUT | Motor Imagery- BCI Performance |  | ✓ | ✓ |  | ✓ |  |
| Witte et al., (2013; Table 1:16); KUT | SMR-BCI performance |  | ✓ | ✓ |  | ✓ |  |
| Susceptibility to anger: | Marxen et al., (2016; Table 2:3); Emotional Contagion Scale | fMRI-based neurofeedback, emotional regulation |  | ✓ | ✓ |  | ✓ |  |
| Zotev et al. (2011; Table 2:5); Emotional Contagion Scale | fMRI-based neurofeedback, emotional regulation |  | ✓ | ✓ |  | ✓ |  |
| Symptom severity | Nicholson et al., (2017; Table 2:4); Clinically Administered PTSD Scale | fMRI-based neurofeedback, emotional regulation | ✓ |  | ✓ |  | ✓ |  |
| Various Other Factors: Cognitive style, tension learning style, motivation, perceived session difficulty, the big five personality traits and mindfulness, Pain specific coping strategies | Juenet et al., (2015; Table 1:8); Various | SMR-BCI | ✓ | ✓ | ✓ |  | ✓ | ✓ |
| Kikkert (2015; Table 1:9); Various | Beta enhancement, Theta inhibition | ✓ | ✓ | ✓ |  | ✓ | ✓ |
| Emmert et al. (2017; Table 2:2) Coping Strategies Questionnaire | fMRI-based neurofeedback, pain management |  | ✓ |  | ✓ | ✓ | ✓ |