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In Neurofeedback Training, Harder is Not Necessarily Better: The Power of Positive Feedback in Facilitating Brainwave Self-Regulation

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Abstract

Neurofeedback is gaining recognition as an efficient, effective treatment for a variety of different psychological and neuropsychiatric disorders. Its value has been shown in robust clinical studies. However, a certain percentage of clients do not respond to this treatment modality. We suggest performing easier sessions so that clients receive an increased rate of positive feedback. This may encourage positive response to neurofeedback. Research has shown that implicit learning, the type of learning involved in neurofeedback, is better achieved with high levels of positive feedback. In addition, psychological factors related to attention, motivation, cooperation, and positive affect may also be contributing to this facilitatory effect. The relevant theoretical background and supporting evidence are provided.

Keywords: neurofeedback; EEG-Biofeedback; implicit learning; basal-ganglia; threshold; thresholding; reward; positive feedback

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Background

EEG neurofeedback (also known as EEG-biofeedback or brainwave self-regulation) has been used to treat a variety of neuropsychiatric disorders (Niv, 2013). Success rates vary and have often been reported to be high, but invariably some trainees are slow to respond or do not show any response to this treatment modality (Rogala et al., 2016; Zuberer et al., 2015). Indeed, nonresponse rates were reported to vary between 16% and up to 57% in some cases (Alkoby et al., 2018). The reasons for this nonresponse are not yet well understood (Oblak et al., 2019). Part of it may be due to the use of standardized protocols that do not target the individual dysregulation in these studies. Other methodological factors may be responsible for these rates of nonresponse, such as number and length of sessions, intersession intervals, type of threshold used (automatically vs. manually adjusted), trainer-participant interface (Gruzelier, 2014), as well as schedules of reinforcement (Sherlin et al., 2011) and types, and modalities of feedback (Strehl, 2014). The ability of the clinician to instill a motivation to succeed in the client has also been cited as crucial (Sterman & Egner, 2006). As neurofeedback is gaining increasing acceptance and recognition by the mainstream medical establishment, it is important to elucidate the factors and parameters that can facilitate learning and enhance treatment results.

Neurofeedback is based on the principles of operant conditioning of brainwave activity (Birbaumer et al., 2013; Collura, 2014; Sitaram et al., 2017). Clients are fed back information about their electrophysiological activity and are taught to modify this activity by means of positive and negative feedback received through the sensory modalities (i.e., visual, auditory, or tactile feedback). When a client's brainwave activity comes closer to the desired target activity (usually, age-group norms), alleviation of neuropsychiatric symptoms often ensues. The very act of learning to regulate one's brainwave activity may rid clients of mental barriers that have plagued them for years, and, albeit rarely, this may even happen in the course of just two sessions (van der Kolk, 2014).

An average neurofeedback training series may take anywhere between 40 and 80 sessions (Barabasz & Barabasz, 1999), with some individuals requiring more sessions to obtain satisfactory results. In some cases, part of the reason the process takes a long time is that it is not always obvious which training protocols would be most effective for a given client, even when the protocol selection is based on a neurometric assessment (i.e., qEEG test), intake, and a thorough anamnesis. Practitioners normally start with one or two training protocols for a few sessions based on these assessments. They monitor the client's response, and either continue with the initial protocols, if response is satisfactory, or change to other protocols, if there is no response or if the response is less than optimal (Fisher, 2014; Johnson & Bodenhamer-Davis, 2009). When clients are fast responders, fine-tuning of the protocol selection process can be accomplished more rapidly. However, when clients take a long time to respond—with some, it may require 20 or more sessions before we can notice and start appreciating the effects of the training (Pallanti, as cited in Gastaldi, 2023)—then the practitioner's job of fine-tuning the protocol selection process is more difficult and requires more time. Practitioners may also wonder in such cases whether the client is a nonresponder to neurofeedback, or whether the problem is with the protocol they selected. Speeding up clients' response in such cases may aid the process.

Thresholding plays a crucial role in this respect. It has already been suggested that setting thresholds optimally may save up to 35% of the overall training time, which may be translated into significant reductions in training costs for clients (Davelaar, 2017). Here we suggest that performing training sessions with thresholds yielding relatively high success rates (and therefore a high incidence of positive feedback) may accelerate clients' neurofeedback learning and response. In other words, when performing neurofeedback sessions, clients should receive more positive than negative feedback to achieve success in training. To explain this, we should first refer to some basic theoretical principles of learning, and more specifically, of reinforcement learning or operant conditioning.

Basic Behaviorist Principles of Learning

Thorndike (1911, as cited in Sherlin et al., 2011) first formulated the Law of Effect, which states that reward raises the likelihood that the target behavior will reoccur while punishment decreases that likelihood. Skinner further developed the idea of operant conditioning based on this law (Skinner, 1945).

The neural correlates of reinforcement learning, or operant conditioning, are varied. Learning from reward seems to involve partially different networks and structures than learning to avoid punishment (Elliott et al., 2010). Dopaminergic neurons in the striatum and frontal cortices (Bromberg-Martin et al., 2010) as well as in the substantia nigra and ventral tegmental area (Sulzer et al., 2013) seem to play a key role in reward learning. Learning to avoid punishment involves the insula and lateral orbitofrontal cortex, among other regions (Elliott et al., 2010; O'Doherty et al., 2001; Wächter et al., 2009).

There are positive and negative rewards, and positive and negative punishments. Positive rewards are when we provide something desirable to an organism to increase the targeted behavior. Negative rewards are when we remove something undesirable from the organism with the intention of increasing the targeted behavior. Positive punishments are when we give or do something unpleasant as punishment to decrease the likelihood of a certain behavior. Negative punishments are when we remove something desirable from the organism with the intention of decreasing the likelihood that a certain behavior will reoccur (Sherlin et al., 2011).

For simplicity's sake, in this paper we employ the broader terms of positive feedback and negative feedback to refer to rewards and punishments, respectively, without resorting to the more refined categories based on the types of reinforcers employed. That is, here positive feedback refers to either positive or negative reward, and negative feedback refers to either positive or negative punishment.

There are different neurofeedback technologies, with various methods of providing feedback to clients, employing positive feedback, negative feedback or a combination of both. Since clients often know that the absence of positive feedback is really negative (i.e., it means that their brainwaves are not reaching the target activity), the absence of such positive feedback may be experienced by them as negative feedback, an indication of failure. In such cases, this would serve as an internal, or secondary, punishment. The opposite is true as well: the absence of negative feedback may be perceived by clients as rewarding, an indication of success, even if no reward is actually obtained. In this case, this would serve as an internal, or secondary, reward.

Thresholds and Success Rates in Neurofeedback Training

In neurofeedback, different aspects of brainwave activity can be trained up or down. Amplitude, coherence, percent time, and symmetry indices are just few examples of neural activity that can be trained and modified through neural feedback. Here we refer to amplitude training, but the same principles may hold true for other aspects of neural activity as well.

Brainwaves are referred to in terms of their frequency and amplitude. Frequency is the number of cycles per second, measured in units of hertz (e.g., theta: 4–8 Hz, alpha: 8–12 Hz, etc.). Brainwave amplitude refers to magnitude, measured in units of microvolts. Amplitude in any given brainwave frequency is determined by the degree of synchronization of neurons at that specific frequency under a certain electrode site (Daffertshofer & van Wijk, 2011). When we attempt to enhance a frequency and train its amplitude up, for example, we set a certain value as the "threshold": every time the brain produces this frequency at amplitudes that are at or higher than the threshold, the client receives positive feedback, and every time the brain produces amplitudes that are lower than this threshold, the brain receives negative feedback. The opposite is true for frequencies we attempt to suppress. In such inhibit frequencies, the client receives positive feedback for amplitudes at or below the threshold. The threshold determines the difficulty level of the training. If placed high in reward protocols, or low in inhibit protocols, it may yield relatively low success rates, which translates to a lower incidence of positive feedback provided to clients.

There are different ways of setting training thresholds (Vernon et al., 2009). A threshold can be a fixed value. This fixed value can be preset, based on previous experience, previous results of the client, or professional literature, or it can be equal to the average amplitudes at rest or a proportion of this average; alternatively, it can be a changing value designed to yield a fixed success rate (i.e., automatic threshold). A common perception among clients and clinicians, especially those new to neurofeedback, is the harder the training, the more efficient it is. The tacit assumption here is the brain is like a muscle, and the more "weights" we load onto it, the better the results. Sessions conducted under this assumption may therefore yield success rates of around 30–40% or lower. That is, clients would meet the target brainwave activity or go beyond it in the desired direction only around 30% or 40% of the time or less, and the rate of compensation would be accordingly low.

In this paper we would like to suggest setting the threshold so it yields higher success rates. This will yield a higher incidence of positive feedback during a session, which is preferable, as it may yield more robust clinical results, faster.

The Power of Positive Feedback

As mentioned above, one common way of setting a threshold is to place it at exactly the average amplitude at baseline. Thus, the client's brainwave activity at rest would go above this value roughly 50% of the time. Here we suggest setting a threshold that is easier to pass (i.e., a lower threshold in reward frequencies or a higher threshold in inhibit frequencies). This would be one yielding significantly more than 50% success rates. We believe this is preferable, as it may contribute towards a more effective and efficient training. The reasons for this are physiological and psychological in nature, as detailed below. To explain this, we would use a simple protocol as an example, sensorimotor rhythm (SMR) up at CZ, but the same rationale may hold true for other, more complex protocols as well.

In an SMR up protocol, if we use the average amplitudes at baseline as the threshold, we provide negative feedback to clients every time the amplitude is below, or even just below, what it was at baseline. However, when we do this, we basically provide the brain with negative feedback for producing SMR activity that is very close to the desired level, even if it does not meet it. This may make it harder for the brain to learn the desired pattern of activity and in some cases may even teach the brain to inhibit it. It was noted in a different context that if positive feedback is withheld for an activity falling just short of the threshold, this may discourage the increase of the desired brainwave activity (Hardt & Kamiya, 1976).

According to the principles of shaping, we reward the brain not only when it meets the criterion (i.e., threshold), but also when it comes close to it. This way, we indicate to the brain the direction it has to shift its activity in order to receive positive feedback. Activity very significantly distant from the target should not be rewarded, so the brain does not unlearn the desired pattern of activity (Davelaar, 2018). One of the problems with negative feedback is it carries little specificity, which makes it harder for clients to know how to improve (Reinschluessel & Mandryk, 2016). Positive feedback, on the other hand, contains such information. While this practice is accepted by some for the first stages of training, here we suggest that not only at the beginning of neurofeedback training but throughout the training series, clients should preferably receive more positive than negative feedback when training.

Ideally, there should be a gradation of feedback, so activity that is very far from the threshold receives more negative feedback than activity somewhat closer to the threshold. In many neurofeedback systems such gradation exists. Ideally, as the brain learns the desired pattern of activity and produces higher and higher amplitudes on average, the new thresholds should be updated accordingly, but still allow for higher percentage of positive, compared to negative, feedback.

How do we set the thresholds? The optimal threshold setting is unknown (Davelaar, 2017) and this question remains to be determined in controlled experiments. Experience shows setting the threshold to around 60–80% of the average amplitudes at baseline in reward frequencies, and between 120% and 140% of the average amplitudes at baseline in inhibit frequencies, may be safe and effective in encouraging the brain to change its electrophysiological activity in the desired direction (Egner et al., 2004; Ros et al., 2009; Vernon et al., 2009). Success rates at such sessions may be 60–80%, which is more informative to the brain than the 50% or so normally achieved when the threshold is set to be equal to the average amplitudes at baseline (Nam & Choi, 2020). More research must be conducted to determine the optimal level of thresholds (Vernon et al., 2009). This observation finds support also when considering the nature of the learning process in neurofeedback, as we explain next.

Implicit Learning is Better Achieved With Positive Feedback

Neurofeedback is a form of implicit, procedural learning, a type of skill learning that can be acquired even without conscious awareness (Birbaumer et al., 2013; Ramot et al., 2016; Siniatchkin et al., 2000; Sitaram et al., 2017). The neural network engaged in neurofeedback is wide and involves both cortical and subcortical structures. Among these, the basal ganglia seem to play a major role as a part of the corticostriatal loop (Birbaumer et al., 2013; Emmert et al., 2016; Koralek et al., 2012; Lam et al., 2020; Skottnik et al., 2019), with dopaminergic and glutamatergic synapses (Sitaram et al., 2017). These nuclei are involved in other types of implicit learning as well (Heindel et al., 1989; Poldrack et al., 2001). Their involvement in neurofeedback was demonstrated in both human functional magnetic resonance imaging (fMRI) studies (Emmert et al., 2016; Sitaram et al., 2017) and animal studies (Koralek et al., 2012; Schafer & Moore, 2011).

Research has shown implicit learning is better achieved with correct feedback than with error feedback—that is, with positive, rather than negative feedback (Loonis et al., 2017). The reason for better implicit learning with less error feedback (or “errorless learning”) may be that errors cause people to use explicit cognitive processes in trying to form better strategies for success. This may overload the system and, paradoxically, impair implicit learning (Chafee & Crowe, 2017; Maxwell et al., 2001; Poolton et al., 2005). Loonis and colleagues found category-saccade learning, a type of implicit learning, improved more after correct choices and positive feedback than after incorrect choices and negative feedback. They found negative feedback in this type of task appears to interfere with the learning process: performance worsened after an incorrect trial and subsequent reaction times increased. In equivalent explicit learning tasks, performance was almost the same after positive and negative feedback (Loonis et al., 2017). Interestingly, Sasaki et al. (2010) suggested successful performance of a visual perceptual learning task, a form of procedural learning, yields a sense of achievement. This serves as an internal reward, as opposed to an externally provided physical reward. This internal reward, in turn, reinforces the implicit learning of task-irrelevant features, which are presented simultaneously as the task-relevant features (i.e., implicitly). Similarly, Shibata and coauthors found fake, larger-gradient positive feedback enhanced performance on visual perceptual learning more than genuine feedback.

They suggested the same reason: positive feedback was perceived by subjects as a form of praise, and this has implicitly facilitated learning (Shibata et al., 2009). Task-irrelevant learning may occur only if the irrelevant stimuli or features are presented subliminally, so the conscious attention system does not detect them (Tsushima et al., 2008). The evaluation of one's performance by the feedback provided seems to be performed by the frontal cortex, and this evaluation directs the basal ganglia and part of the forebrain to control the rate of implicit, perceptual learning (Shibata et al., 2009).

This phenomenon is also demonstrated with amnesiacs, in whom the hippocampus is damaged. The ability of such patients to acquire explicit learning is compromised, whereas their ability to acquire implicit learning is relatively intact. Amnesia patients perform skill learning, a type of implicit learning, better when correct (positive) rather than error (negative) feedback is emphasized (Evans et al., 2000). In this case, however, an alternative explanation may be that amnesiacs have difficulty remembering and employing explicit cognitive strategies. They therefore perform better with "errorless learning" than with "errorful learning." Also, off-medication Parkinson's disease patients, who have basal-ganglia damage, learned procedural tasks better when punishment was employed as feedback rather than reward (Argyelan et al., 2018). Once back on medication, dopamine medications changed this pattern, so the patients acquired procedural learning better from reward than from punishment. This may stress the importance of the basal ganglia, a key component in neurofeedback learning as well, in acquiring procedural learning from positive feedback or reward.

Neurofeedback is considered by most an implicit form of learning (Lam et al., 2020; Ramot et al., 2016; Siniatchkin et al., 2000). Since implicit learning is better achieved with positive feedback, this may yield further support to the observation that neurofeedback sessions should be conducted with a relatively high incidence of positive feedback. Sessions conducted this way may be more efficient and effective than sessions conducted with equal or higher incidence of negative feedback.

Maxwell and colleagues suggested errorful learning relies more on explicit processes and involves hypothesis testing about different strategies (Maxwell et al., 2001). Kober and coauthors proposed testing of strategies for success in neurofeedback imposes a cognitive load on trainees, which may harm their performance. They advise that neurofeedback training is better performed without employing such conscious, explicit strategies (Kober et al., 2013). Lam and colleagues found error monitoring networks are of lesser relevance to neurofeedback learning (Lam et al., 2020), which again stresses the fact that neurofeedback may be based more on learning from positive feedback than error feedback. Naturally, a certain percentage of negative feedback is necessary, but more positive than negative feedback is preferable.

Some Additional Considerations in Favor of Employing High Rates of Positive Feedback

To be effective, positive feedback should preferably be provided more often than negative feedback. This would be the case when we set the threshold lower than the average baseline amplitudes for reward frequencies, and higher than average baseline amplitudes for inhibit frequencies. In addition to the physiological and learning-related aspects discussed above, there are also psychological considerations in favor of employing more positive than negative feedback in neurofeedback training sessions.

When the session is too difficult, with relatively low levels of positive feedback, clients tend to try to artificially control the feedback. They do so unconsciously by shifting in their chairs, touching the sensors, moving their arms, legs, or facial muscles, or otherwise trying to control the feedback with their muscles rather than with their brainwave activity. This interferes with the session and training process and decreases the chances learning occurs.

It was found that negative feedback may demotivate participants (Reinschluessel & Mandryk, 2016) and make them avoid participating in a task, even when the task is an otherwise enjoyable game (Lin et al., 2006). When clients are children, they may refuse to continue a neurofeedback session, without being able to verbalize the reason for their refusal. This may affect their motivation to complete the remainder of the training series. Some adult clients, especially people who are anxious or depressed, tend to judge themselves harshly for their performance. If such clients believe they are not receiving enough positive feedback, they tend to interpret it as if they are failing to perform the training satisfactorily. This may cause them to be stressed, tense, and anxious and, as a result, they may try to control the feedback by exerting excessive mental effort. As mentioned earlier, such an effort may be counterproductive. Kober et al. (2013) have shown exerting mental effort and trying to consciously control the feedback causes cognitive overload that may hamper learning. This could also cause fatigue relatively early in the session, which is counterproductive for successful training (Shourie et al., 2018). The optimal way of training appears to be by releasing conscious control, keeping an open focus, and letting the brain naturally process the feedback and respond to it (Fehmi & Robbins, 2008). To ensure this, clients must be relaxed, and this state cannot be achieved when clients receive a high rate of negative feedback.

Clients may be more comfortable and motivated to cooperate when thresholds are easier to pass. A high incidence of positive feedback boosts their confidence, and this may have a beneficial effect on their motivation, cooperation, and consequently, on their overall success in the training (Van Doren et al., 2017). Positive feedback produces signals of internal reward, and this in turn may enhance implicit learning (Sasaki et al., 2010). Even when the positive feedback is false, it may still boost learning, for the same psychological reasons (Shibata et al., 2009). In support, motivational factors were positively correlated with Brain-Computer Interface (BCI) performance (Barbero & Grosse-Wentrup, 2010; Nijboer et al., 2010). Motivation and mood were found to be at least moderate predictors of success in neurofeedback and BCI training (Cohen Kadosh & Staunton, 2019).

Attention is another factor crucial for neurofeedback learning. Setting the threshold too high in reward protocols, or too low in inhibit protocols, so the difficulty level is high and the incidence rate of positive feedback is low, may harm the client's ability to be attentive for the duration of the session and interfere with the learning process (Cohen Kadosh & Staunton, 2019).

In summary, if the threshold is set so the training difficulty level is high, then too little feedback information is provided for the brain to learn from. This may frustrate clients, demotivate them, hamper their mood, and may be too taxing for them in terms of their attention resources. Clients may try to control the feedback with their muscle activity and even refuse to continue training, if too little positive feedback is provided. This is especially true for the first few sessions a naïve neurofeedback client performs but is also true for more experienced trainees as well. Working with thresholds yielding higher success rates and higher incidences of positive feedback may be preferable. This is particularly the case with young children or anxious adults. This may allow for better learning and better clinical results. However, if the threshold is set so the session is too easy, this may be counterproductive. Both too little and too much positive feedback may inhibit clients' ability to learn to self-regulate (Vernon et al., 2009).

Supporting Research and Evidence

Support for the observation that thresholds yielding a higher incidence of positive feedback are preferable comes from clinicians and researchers, who have employed such thresholds. For example, Thompson and Thompson (1998) stated that for reward frequencies, the threshold is set 0.2 to 0.6 microvolts lower than the client's average, whereas for inhibit frequencies, the threshold is set 1 to 2 microvolts higher than the client's average. Others have placed the threshold at 80% of the baseline average of the reward frequency, and at 120% and even 160% of the baseline average of the inhibit frequency (Egner et al., 2004; Ros et al., 2009). Ros et al. (2017) used thresholds that yielded 60% positive feedback and 40% negative feedback. Lubar suggested when clients get stuck on a plateau in their learning curve and show no progress in neurofeedback training, to set the threshold lower, so that they receive more positive feedback (Ayers et al., 2000). Van Doren and coauthors showed that when ensuring clients receive at least 50% positive feedback during neurofeedback, their performance improves compared to thresholds yielding lower reward incidence in an alpha-theta protocol (Van Doren et al., 2017). Others reported using at least 70% positive feedback (White & Richards, 2009). In addition, Davelaar (2017) found in a computational analysis of a neurofeedback protocol that lower (that is, "easier") thresholds were associated with faster learning and higher (that is, "tougher") thresholds were associated with unlearning the target pattern of activation. Vernon et al. (2009) noted that, in studies employing alpha enhancement protocols, thresholds have been placed anywhere between 50% and 85% the amount of alpha seen at rest. This makes training easier than with a threshold set at 100% the average amplitude at baseline (Vernon et al., 2009). In reference to Knox (1980), who suggested a range of possible thresholds, Vernon and colleagues noted that thresholds exceeded by 75% during resting baseline period would probably be both easier and more effective for training than thresholds exceeded by lower percentages, because with higher percentages clients receive more feedback information (Vernon et al., 2009).

A recent pioneering study by Nam and Choi (2020) has yielded empirical results lending support to this thesis. The researchers found in an SMR enhancement session, setting the training threshold so subjects receive more reward (80% reinforcement rate) was more effective than setting it so subjects receive less reward (50% and 30% reinforcement rates).

An fMRI study revealed that during the first training session, neurofeedback signals of failure (i.e., negative feedback) were correlated with deactivations in the precuneus/posterior cingulate. Neurofeedback signals of success were correlated later in the process with deactivations in the medial prefrontal/anterior cingulate cortex (Radua et al., 2018). The level of deactivation in the anterior node predicted the efficacy of the training in reducing anxiety. These results indicate a higher sensitivity to signals of failure at the beginning of neurofeedback learning and to signals of success later in the learning. In the earlier stages of neurofeedback learning, clients may be apprehensive about their ability to learn from feedback and may consequently try to control the feedback consciously. Later, but still at an early stage of learning, this kind of learning diminishes, and learning from positive feedback takes the leading role in the training process. The only predictor of neurofeedback success in Radua et al.'s (2018) study was the level of deactivations in the anterior node. For most participants, this shift occurred as early as the middle of the first session. This study yields further support to the observation that learning from positive feedback has a central role in neurofeedback.

During operant conditioning, following the delivery of reward, an alpha-like activity called postreinforcement synchronization (PRS) occurs (Collura, 2014), the amount of which is related to the speed of learning (Marczynski et al., 1981). It was previously suggested that meaningful information is too difficult to extract from complex neurofeedback games, and such games do not allow for PRS to occur (Sherlin et al., 2011). Employing the same reasoning, it may be the case that neurofeedback training that is too difficult (i.e., does not provide enough positive feedback), may not allow for the PRS complex to occur and therefore may hamper learning. Indeed, it was demonstrated that cognitive tasks of high-load (Sterman et al., 1993) or low-desirability of the reward (Clemente et al., 1964) interfere with PRS.

There have been researchers who placed the threshold above the average amplitudes at baseline in reward frequencies and below the average amplitude at baseline in inhibit frequencies so success rates and reward incidence were lower (Sterman & Egner, 2006). It has been claimed that placing the threshold this way may make the training tedious for clients (Othmer, 2009). In addition, in terms of information-theory, the brain may not receive enough feedback information to work with. Increasing the reward incidence makes the session more rewarding and engaging, and the training more efficient (Othmer, 2009).

Some have objected, on theoretical grounds, to employing very high reward rates, but admit training this way yields good clinical results (Othmer, 2009). Still, it is important not to “choke” the system. The threshold should not be set so low that we would be rewarding too little of the desired activity, because we would then be training the brain to inhibit the desired activity. It has been shown in other contexts of learning that when clients can earn very large rewards, this harms their performance level (i.e., the “choking” effect of very large rewards; Mobbs et al., 2009). The striatum may be involved in this phenomenon (Chib et al., 2012), which seems to have a dopaminergic basis (Mobbs et al., 2009).

Summary and Discussion

The importance of feedback parameters to the success of neurofeedback training cannot be overrated. The way the threshold is set has a crucial effect on learning in neurofeedback (Vernon et al., 2009), and placing the threshold too high or too low may yield either no response or a response opposite to the desired target behavior (Davelaar, 2017). Debates about thresholding have been continuing for quite some time. Despite the importance of thresholding, there is not enough research on the topic (Nam & Choi, 2020; Van Doren et al., 2017; Vernon et al., 2009).

Different types and modalities of feedback yield different levels of success in training. Feedback can be visual, auditory, or tactile; it can be proportional or binary, immediate or delayed, simple or complex. Visual feedback that is proportional, immediate, and simple seems to better support learning (Strehl, 2014). There are also different schedules of reinforcement (e.g., continuous or intermittent; Sherlin et al., 2011) and research is continuing to determine which may be more effective. Feedback can be provided in different ways and affect clinical outcomes. Regardless of the feedback method selected, a higher rate of positive feedback (i.e., more positive than negative feedback) may be preferable.

Neurofeedback is considered an implicit form of learning (Birbaumer et al., 2013; Emmert et al., 2016; Sitaram et al., 2017). Research has shown implicit learning is better acquired when more positive than negative feedback is given to participants (Loonis et al., 2017). In fact, the power of positive feedback is so strong, that even false positive feedback may enhance learning (Sasaki et al., 2010; Shibata et al., 2009). In addition, psychological factors related to motivation, positive affect, mood, self-confidence, and attention contribute to this phenomenon as well (Barbero & Grosse-Wentrup, 2010; Cohen Kadosh & Staunton, 2019; Curran & Stokes, 2003).

Higher levels of positive feedback in the initial stages of training are in accordance with the principles of shaping (i.e., even behaviors that do not meet the target are initially rewarded). But it seems that in neurofeedback, like in other forms of implicit learning, clients should receive more positive than negative feedback not only at the beginning of training but also in later stages of the training series. If the threshold is set so that it is relatively easy to pass and produces larger rates of positive feedback, implicit learning is more easily acquired, clients are more motivated and cooperative, and training becomes more effective and efficient. This may facilitate and shorten the process of fine-tuning the protocol selection process and help clients acquire brainwave self-regulation faster. It may therefore decrease the amount of time required to achieve the training goals. It may also prevent clients from dropping out due to lack of initial response. Utilizing a 10-minute-long session design, Nam and Choi (2020) have provided some preliminary empirical evidence that higher success rates in neurofeedback yielded better results. Research should be conducted to empirically validate the observation that in longer sessions and in later stages of the training as well, higher levels of positive feedback should be employed to achieve more efficient learning.

Reward alone may be less effective than a combination of reward and punishment (Klöbl et al., 2020). Having punishment is motivating too—the motivation to avoid it—and is important for learning (Mohammadi et al., 2018).

There are some accounts that different personality types respond differently to negative and positive feedback (Frank et al., 2005). For example, extroverts learn better from positive feedback and introverts learn better from negative feedback (Boddy et al., 1986). This distinction has not yet been given sufficient attention in neurofeedback research. Experience shows both personality types seem to benefit from neurofeedback training with relatively high rates of positive feedback, probably due to the implicit nature of neurofeedback learning.

Given the importance of positive feedback in neurofeedback training, it is possible some studies that did not find a robust effect for neurofeedback were employing thresholds yielding lower levels of positive feedback. Thus, information about the way thresholds were set and consequent success rates should be provided in neurofeedback research studies (Van Doren et al., 2017).

Some studies that used automatic thresholding to keep a high reward rate constant (80%) failed to find any specific effects for neurofeedback (Lansbergen et al., 2011; Logemann et al., 2010). The problem in such studies may not lay with the high reward rate, but with the fact that the threshold was automatically adjusted every 30 seconds to keep this rate constant. With such settings, no matter what the clients were doing, they were rewarded at the same rate, which may have, in fact, trained them in opposite directions at times (Ayers et al., 2000; Sherlin et al., 2011).

Using positive reinforcement in neurofeedback games is more efficient than using negative reinforcement (Reinschluessel & Mandryk, 2016). A plausible strategy for training in neurofeedback systems that use negative reinforcement (e.g., systems in which the game freezes when brainwaves do not meet the target) may be to reframe the feedback by asking clients to view the negative state (i.e., the frozen game) as the default state, and the removal of this state as a reward for their achievements.

Lastly, research should be conducted to determine whether a higher rate of positive than negative feedback is effective in all types of protocols and frequency bands or only in some of them; in all kinds of neural indices or just in part of them; with all forms of neurofeedback or only with specific feedback modalities; for all clients or for only specific clinical populations or personality types. Once these questions are empirically answered, the field of neurofeedback may take a substantial leap forward.

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