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Predictors of neurofeedback efficacy: An exploratory study to the influence of personality and cognitive characteristics on the efficacy of theta and beta neurofeedback training.

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Abstract

Background: Although neurofeedback training (NFT) has been receiving increasing attention and support outside the research context, research on the underlying mechanisms is scarce. In this exploratory study, we aim to elucidate some of the factors that may relate to differences in people's ability to achieve successes in NFT. In this paper, we explore the relationship between personality and certain cognitive characteristics, and within and between session EEG change. ***Methods****:* participants were assigned to a theta inhibition protocol (N=10), a beta enhancement protocol (N=10), and a random feedback control condition (N=9). They received eight neurofeedback sessions and completed several psychometric questionnaires and a cognitive styles test. The results were analysed using ANOVAs and multilevel models. ***Results:*** Despite limitations in our interpretation due to the small sample size, we found evidence that electro-encephalographic change in beta enhancement correlates with learning style, cognitive style, and locus of control. Theta inhibition correlates with factors such as mindfulness and reward sensitivity. Our data revealed that within-session manipulation of the targeted frequency, does not necessarily lead to long-term changes in amplitude and that both types correlate with different factors. ***Conclusion***: differences in cognitive characteristics should be taken into account when applying neurofeedback training to different individuals as they may facilitate or hamper certain elements of the learning process.

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1. Introduction

1.1 Neurofeedback

Synchronous electrical activity of neurons, in particular that of the pyramidal cells in the cortex, is reflected in the electro-encephalogram (EEG). Cognitive processes such as attention, problem solving, idea generation, concentration, motor inhibition and control, have been associated with the strength of (de)synchronization in cortical oscillatory activity in specific frequency bands (Basar et al., 2001, Vernon, 2005). To some extent, such cortical activity can be modified through principles of operant conditioning in a technique known as EEG biofeedback or neurofeedback training (NFT). By using a basic EEG setting, which is translated into a simplified visual or auditory representation on a computer screen, one can promote the enhancement or inhibition of activity in certain frequency ranges. During the training, this simplified representation of one's brain activity is fed-back to participants and positive reinforcement allows them to learn to manipulate it. Positive feedback is provided if the participant is able to identify and recreate mental states associated with up- or down-regulation of that frequency (Dempster & Vernon, 2009; Egner & Gruzelier, 2001). Neurofeedback is a promising method to enhance cognitive performance and provides an alternative treatment for certain mental disorders. It is non-invasive, not expensive and valuable in a clinical context. In the past decade, several studies have demonstrated effectiveness in clinical use. For instance, enhancement of the SMR band (13-15 Hz) or lower beta frequencies (15-18 Hz), combined with inhibition of theta activity (4-7 Hz) has proved to be successful in attenuating symptoms of attention deficit hyperactivity disorder (ADHD) (Lubar et al. 1995; Arns, de Ridder, Strehl, Breteler & Coenen, 2009; Gevensleben et al., 2009; Lofthouse, Arnold, Hersch, Hurt & DeBeus, 2012). Training to manipulate the EEG rhythm has proven useful to reduce epileptic seizures (see Sterman, 2000), anxiety and depressive symptoms (Hammond, 2005; Moradi et al., 2011), and schizophrenic symptoms (Gruzelier, Hardman, Wild & Zaman, 1999). In these clinical contexts, the goal of NFT is to normalize the EEG spectrum, yet beneficial effects are found in the normal population as well. Studies have demonstrated that NFT in the normal population is associated with improvements in attention and working memory performance (Egner & Gruzelier, 2001; Keizer, Vermont & Hommel, 2010; Vernon et al., 2003), task-switching (Enriquez-Geppert, Huster & Herrmann, 2013), intelligence performance (Keizer et al., 2010b) and creativity (Gruzelier, 2009).

However, while reading through the neurofeedback literature, one will notice the variety of methods applied in different studies. Training protocols do not consistently result in improvements in cognitive performance. Even within the same protocols, not every subject is able to learn to manipulate their EEG, as the reported number of non-responders in several studies shows (Gruzelier, 2014). It thus appears that the mechanisms underlying training efficacy at the individual level remain largely unknown. The main question to be explored in this study pertains to the correlations of such interindividual differences in personality or cognitive characteristics with the sensitivity to NFT.

1.2 The neurofeedback training protocol

A problem regularly met in NFT is the variability in people's ability to acquire a certain degree of control over their brain activity. Little is known of how these individual differences arise and what enables one person to learn better or faster than the other. These differences may exist in internal and external factors. Variability in external factors can be found by comparing the design of training protocols between studies. To date there is no consensus on the parameters that should lead to an effective NFT protocol (Enriquez-Geppert, Huster, & Herrmann, 2013). The duration of sessions applied in different studies can vary within a range of 30 to 60 minutes. The number of sessions can differ from 5 to more than 40 (Lofthouse et al., 2012; Hammond, 2005). Even after only a single enhancement session of alpha (posterior oscillations at 8-12 Hz) or training of the µ-rhythm (transient sensorimotor oscillations at 8-13 Hz), changes in activity in the cingulate cortex have been demonstrated with functional magnetic resonance imaging (fMRI) (Ros et al., 2013, 2014). Spacing of sessions over time also differs, but most studies involve two or three sessions a week (Lofthouse et al., 2012; Hammond, 2005). Even training frequency bands vary in width and range amongst studies. Sometimes several frequencies are trained simultaneously, as in SMR or Beta1 enhancement paired with theta inhibition training, while other researchers argue that training a single frequency is more effective. Furthermore, researchers can employ a variety of forms of feedback, some using visual feedback such as games, dynamic shapes, or videos, and others use auditory feedback or a combination of both.

All of the above may affect the efficacy of the training and there is increasing awareness that the effects of changing such parameters should be explored further. However, in this study, I have focused on a related question that has not yet been addressed: what is the underlying mechanism that leads to individual differences in the neurofeedback learning process and people's ability to master the technique, even within the same training protocol? As research on internal factors that affect NFT in this field is scarce, I have derived most of my hypotheses from personality theories and literature on individual differences in learning in general. Neurofeedback is a learning process and, like in any other learning process, both external and internal factors contribute to learning ability and success. A necessary step to improve NFT is to further explore the neurofeedback learning trajectory and its interaction with the learning environment as well as individual differences. With this study, I have made a first attempt by exploring possible relationships between neurofeedback training efficacy and individual differences known to affect learning in contexts similar to the neurofeedback setting.

1.3 Research questions and hypotheses

The main purpose of this study is to explore the interaction between neurofeedback learning and individual differences in cognitive style, learning style, personality traits, sensitivity to reward, and mindfulness (the ability to non-judgmentally focus on one's sensations, emotions, and thoughts).

The literature suggests high interindividual variability in the ability to manipulate their EEG, as well as in the shape their learning curve takes (Gruzelier, 2014). One of the distinctions recently made is that of the ability to actively manipulate one's EEG during training vis-à-vis the ability to achieve a more long-term change that shows in increased or decreased amplitude in the training frequency during resting state EEG measurements. These two effects are referred to as phasic and tonic changes in EEG. Phasic EEG change refers to (de)synchronization in a frequency during training itself. By tonic EEG change I refer to a more lasting change in resting state EEG, possibly related to the concept of a consolidation phase often mentioned in theories of motor learning (Newell, Mayer-Kress, Hong & Liu, 2009), a process that is in its essence similar to neurofeedback learning. In a report reviewing the evidence for the effect of neurofeedback in enhancing performance, Vernon (2005) notes that the ability to induce phasic changes does not necessarily result in clear tonic changes as well. A review by Gruzelier (2014) seems to support this statement. One of the goals in this study is therefore to explore whether the ability to achieve phasic change also leads to tonic changes in EEG. If the two are found to be distinct, I will test whether tonic or phasic learning can be predicted by individual differences in cognitive style and personality characteristics, as described further below.

I hypothesize that factors important to learning ability in general mediate learning in the context of neurofeedback, and possibly differentially for tonic and phasic changes. Although, as mentioned above, factors involved can be external (e.g. form of visual or auditory feedback) or intrinsic (e.g. personality, individuals' normal EEG), in this study I will focus on intrinsic factors. The literature on learning covers a wide range of variables. I have selected some that seem relevant to the specific context of neurofeedback – a context that requires participants to guide their own learning process with very few external cues or directions. Cognitive and learning styles are relevant concepts in this context. It is argued that some people have an innate preference for a structured learning environment and need more external guidance, and there are those who benefit from only receiving a few loose instructions (Rayner & Riding, 1997; Riding & Watts, 1997). The first type of people have a cognitive style often referred to as ‘wholist', ‘intuitive', or ‘field-dependent'. The second type is associated with a preference for ‘analytical', ‘sequential' or ‘field-independent' processing styles. It is hypothesized that having an analytical style correlates with finding the training less difficult and possibly with higher learning ratios.

NFT is built on trial-and-error based learning, hence the importance of participants' sensitivity to reward and punishment, sensitivity to one's internal mental state, and feelings of ability to be in control. Learning in neurofeedback is achieved by reinforcing an increase or decrease in a desired frequency by reward (points and continuation of a video) and punishment (interruption of a video). Motivation theories, such as Gray's reinforcement sensitivity theory (McNaughton & Corr, 2004), account for individual differences in sensitivity to reward, non-reward, and punishment. In this context I will draw on two commonly used sensitivity systems: sensitivity of the behavioural inhibition system (BIS) or activation system (BAS) is thought to explain differential responses to positive (reward) or negative (punishment) feedback (Carver & White, 1994). BIS and BAS dimensions have been found to correlate with theta synchronization in response to feedback content (Balconi & Crivelli, 2010), and may therefore prove relevant in the learning speed of theta training.

In addition, the extent to which participants believe they have some control over the events that happen to them (having an internal locus of control) may find it easier to believe they can actively influence their brain activity, which may facilitate actual electrophysiological changes. Two studies have looked into this. Burde and Blankertz (2006) found support for this theory by assessing specific aspects of locus of control as predictors of brain computer interface (BCI) efficacy. They found that higher scores on a measurement of control beliefs in dealing with technology correlate with better BCI performance. On the other hand, Witte and colleagues (2013) found similar results in the neurofeedback context, but did not include a general measure of locus of control. It would also be informative to see if participants with higher self-awareness and introspective skills find it easier to associate mental states with EEG patterns and adjust their EEG according to the training protocol. It has been found that people with higher scores on self-consciousness or mindfulness are better able to self-regulate in response to stressful life events (Ghorbani, Cunningham & Watson, 2010). A higher ability to regulate one's mental state may also be reflected in the ability to regulate brain states during neurofeedback. This factor may be particularly important in producing phasic EEG change.

Lastly, the five major personality characteristics are often mentioned in the context of learning. The few studies on neurofeedback that have included a measure of personality did not provide clear evidence that it relates to individual differences in performance (Hammer et al., 2012), although the authors acknowledged that one session of BCI training perhaps does not allow a learning process that can be influenced by factors that generally influence human learning. However, Hardman and colleagues (1997) found a correlation between learning to regulate asymmetry in slow cortical potentials (SCPs) and scores on a personality measure of withdrawal in healthy subjects. In the academic context, conscientiousness and openness to experience on the Big Five personality scale are most consistently associated with learning, motivation, and performance (Busato, Prins, Elshout & Hamaker, 1999; Chamorro-Premuzic & Furnham, 2009). Based on this exploration of the learning literature, I suggest to include personality as a factor possibly mediating the learning process.

Alongside these main lines of investigation, the study design allows some exploration of the relationship between individual differences and the spectral EEG irrespective of NFT. This may provide interesting information on the correlation between beta or theta amplitude and personality or cognitive characteristics.

In summary, this study addresses the following four research questions:

1. Did participants enrolled in beta enhancement and theta inhibition training successfully learn to manipulate activity in the respective EEG frequency bands?
2. Is there a relationship between phasic and tonic EEG change? More concrete: does successful active manipulation of the targeted EEG frequency predict lasting change in EEG over sessions?
3. Are there main effects of individual differences on theta and/or beta amplitude (change)?
4. Do individual differences, known to affect learning, affect phasic or tonic EEG change in neurofeedback training?

2. Method

2.1 Sample

Participants were 34 students from Goldsmiths College (London) who signed up to take part in the project with informed consent. Most of the participants were undergraduate psychology students participating for credits and some were postgraduate students from other departments participating for money. The study was approved by the ethical committee of Goldsmiths College and participants all gave their informed consent during the first meeting. Participants were eligible if they had no history of major mental or neurological illnesses. One participant was excluded from further participation after the pre-training EEG session due to an extremely low individual alpha frequency. For two participants we had to discontinue the training after half of the sessions due to personal circumstances that led these participants to miss too many sessions. One participant in the beta training group failed to complete the questionnaires in time. The data of this participant will only be used to answer the first two research questions. We lost neurofeedback data of one participant in the control group. Therefore we excluded this participant from the analyses. The final sample consisted of 29 participants (19 females, eight males, two unknown; mean age = 21.5).

2.2 Procedure

Permission for the study was asked from the ethical committee at Goldsmiths College and from each participant by an informed consent form. Participants were quasi-randomly (by order of enrolment in the study) assigned to one of three conditions: an individualized beta1 enhancement protocol (*n* = 10), an individualized theta inhibition protocol (*n* = 10), or a random neurofeedback protocol that serves as control condition (*n* = 9). We chose these training groups for a project done in conjunction with the currently described study, which aimed to test hypotheses on the effect of protocol-specific training on attention and executive functioning tasks and the ERP P300 component. Participants were not told which frequency band they were training.

Participants received eight neurofeedback training sessions scheduled over three to four consecutive weeks. A week before and after the training sessions all participants underwent EEG recordings to collect baseline EEG. In the context of the current study, only the pre-training resting state EEG (3 minutes eyes open and 3 minutes eyes closed) has been used, to determine protocol settings (explained below). Participants performed an additional computer task to measure cognitive styles during this pre-training EEG session. After the EEG session but before the first training session, participants completed a number of online self-report questionnaires at home to measure pre-experimental individual differences.

2.2.a. Neurofeedback. Participants received eight neurofeedback sessions, each consisting of ten 2.5 minute trials. The first and last trial served to collect baseline data: participants were asked to relax and simply watch the feedback video play. The remaining eight trials were training trials during which participants were asked to actively try to learn from the feedback and gain some degree of control over the amplitude in the frequency they were training. Between trials there was a short break during which participants were asked to indicate on a scale of 1 to 7 how relaxed and concentrated they felt during a trial.

Figure 1
An example of a neurofeedback screen presented to the participant. The upper bar represents activity in the training frequency, the lower bar represents EMG activity. The video, which runs contingent on performance, dominates the screen.

Feedback was provided by means of a screen (Figure 1) that provides a visual real-time representation of the training frequency in the form of a dynamic bar graph that rises and falls with an increase or decrease in amplitude. A second bar graph showed electromuscular (EMG) activity. The focus of the screen was a video, which ran as long as participants kept their activity within a predetermined range and did not produce too much muscular tension. A different video was shown each session, presented in a fully randomized order. Additional positive feedback in the form of reward points was contingent on both EMG activity and the amplitude of the given filter-band.

Based on the first resting-state baseline trial of each neurofeedback session, a threshold was determined for the respective filter-band and the EMG activity. This threshold was adjusted every subsequent trial according to the participant's performance on the previous trial. Feedback through the error bars was directly contingent upon measured EEG activity. Initially, the threshold was always set to 80% of the baseline measurement. In the enhancement of beta and random frequency protocols, this meant that positive feedback was provided as soon as the participant showed amplitude values higher than 80% of the mean amplitude during the first baseline trial (mean*0.80). For the inhibition protocols (EMG, theta, and random frequencies), positive feedback was provided if the participant managed to keep the amplitude below 125% of the mean baseline value (mean/0.80). For each trial, the threshold was adjusted in steps of 5%: if the participant raised amplitude in a trial, the threshold was set to 85% for the next trial, if it decreased, the threshold was set to 75%. Participants were unaware of the height of the threshold, however they could see a change in colour from green to red in the bar graphs if they produced activity outside this range. Participants were always instructed to keep the bar graphs green, the EMG bar as low as possible, and try to keep the video running.

In the beta1 and theta training groups, training frequency bands were set based on the participant's individual alpha frequency (IAF). IAF was determined by finding the peak of power within the alpha activity range during eyes closed resting state EEG (see Klimesch, 1998 for a description of the procedure). Individual beta1 was defined as a frequency range from 2 to 5 Hz above the IAF. Individual theta was defined as a range from 6 to 4 Hz below the IAF. Thus, for someone with a typical IAF of 9 Hz, theta was defined as 3-5 Hz, and beta1 as 14-17 Hz. Participants in the beta1 group trained to increase the amplitude, whereas participants in the theta group trained to decrease the amplitude. Participants in the random feedback group switched each session between enhancement and inhibition of different high (beta3, 23-26 Hz, and beta4, 27-30 Hz) and low (low alpha, 8-10 Hz, and high alpha, 10-12 Hz) frequencies. The order of these protocols was counterbalanced between all participants.

2.3 Instruments

2.3.1 EEG. Before the first and after the last neurofeedback session, a full-scalp 64-channel EEG scan has been conducted using BioSemi equipment with Ag/AgCl electrodes. Two external Ag/AgCl electrodes on the earlobes served as references. Eye blinks were recorded using external electrodes placed above and below the right eye, and horizontal eye-movements were registered by two external electrodes placed outside the outer canthi.

2.3.1 Neurofeedback Apparatus. All neurofeedback training sessions were carried out with EEG Biograph Infiniti 5.1.4 software and ProComp differential amplifier (Thought Technology Ltd, Montreal, QC). Signal was acquired at 256 Hz, A/D converted, and band-filtered to extract individualized training frequencies. The signal was smoothened to facilitate feedback and in some cases we used an amplitude cut-off to reduce heartbeat induced interference. Raw EEG amplitude measures were transformed online into simplified visual feedback in the form of short video clips (around 2.5 minutes = 1 trial) and bar graphs. The video clips were retrieved from the Thought Technology database or selected from the internet and edited to ensure continuous movement and appropriate duration. The feedback was presented via a second monitor placed at 1 meter distance in front of a comfortable chair. Neurofeedback EEG was recorded at Cz, referenced and grounded to the earlobes using three gold electrodes. We aimed to keep impedances below 5 kΩ.

2.3.3 Measures of individual differences.

1. The e*xtended cognitive styles analysis wholist-analytic* (E-CSA-WA*;* Riding, 1991; Peterson & Deary, 2006). This test of 80 visual tasks measures participants' preferred cognitive style. This

test differentiates between people with a more wholistic processing style as compared to those with a preference for an analytic processing style. The CSA uses reaction time and must be administered individually in a quiet room. The test requires the use of a keyboard with specified response keys. The test computes a WA-style ratio. Values close to 0 reflect a wholistic preference and scores closer to 2 or above reflect an analytic preference. The authors of the test found that university students' values typically fall within a range of .97 to 1.25, reflecting little preference (Riding 1991; Peterson et al. 2003, 2005).

2. The *mindful attention awareness scale* (MAAS; Brown & Ryan, 2003). A short 15-item questionnaire measuring open and receptive awareness of and attention to what is taking place in the present. Participants rate the 15 statements on everyday experience based on the frequency they encounter the experience on a Likert-scale from 1 to 6 ('almost always', 'very frequent', 'somewhat frequent', 'somewhat infrequently', 'very infrequently', and 'almost never'). The final score is the sum of all scores, with high scores reflecting high dispositional mindfulness.

3. The *behavioural inhibition/activation scales* (BIS/BAS; Carver & White, 1994) questionnaire measures subjective sensitivity to reward and punishment that reflects participants' tendency to behavioural inhibition or activation. Scores range from 1 to 4, with 1 being 'very true for me'; 2 equals 'somewhat true for me'; 3 equals 'somewhat false for me'; and 4 equals 'very false for me'. The test consists items belonging to one of four dimensions: behavioural inhibition (BIS); behavioural activation drive (BAS drive); behavioural activation fun seeking (BAS FS); behavioural activation reward responsiveness (BAS RR). Scores of items of one dimension are summed to calculate the sum score in the respective dimension.

4. *50-item IPIP big-five personality factors test* (Goldberg, 1992). This free and shorter adaptation of Costa and McCrae's 1992 Big Five personality test, retrieved from the open online international personality item pool (IPIP), has been used to assess participants on the dimensions of extraversion, agreeableness, conscientiousness, openness, and neuroticism.

The test consists of 50 statements such as ‘I am the life of the party’, that needed to be scored on a five-point Likert scale (‘not at all like me’, ‘not like me’, ‘neutral’, ‘like me’, ‘just like me’). Each personality factor is reflected in 10 items, responses were assigned values 1 to 5 and summed to obtain a total score per personality factor.

5. The revised s*tudy process questionnaire 2F* (SPQ; Biggs, 2001) assesses participants' learning style on the dimensions of deep versus surface, approach, and strategy. Of main interest are the constructs of deep versus surface learning, and how they relate to personality traits (mainly openness to experience and conscientiousness). Participants rate how much the content of an item is true of the participant: 1 corresponds to ‘never or rarely true of me’; 2 corresponds to ‘sometimes true of me’; 3 corresponds to ‘true of me half of the time’; 4 corresponds to ‘frequently true of me’; 5 corresponds to ‘always or almost always true of me’. Scores of items belonging to the ‘deep’ dimensions were summed and scores on the ‘surface’ dimension items were summed to obtain the total score for these dimensions.
6. *Rotter's test of external vs internal locus of control* (LOC; Rotter*,* 1966) was used to measure the extent to which a person believes reinforcement to be contingent upon his own behaviour or attributes it to external factors/chance. The test consists of 29 items of two statements, one statement reflects an internal LOC, the other an external LOC (e.g. 1 a: children get into trouble because their parents punish them too much; 1b: the trouble with most children nowadays is that their parents are too easy with them). Participants select the statement that they agree with most. The statement reflecting external LOC receives a point, which is summed over all items. The final score is a value between 0 (extreme internal locus of control) and 29 (extreme external locus of control).

Except for the CSA, which was administered right after the first EEG session in the lab environment, all of these questionnaires were completed before the first neurofeedback training session on a computer at home. Questionnaires were administered online using the online survey software made available by Qualtrics.

In addition to these primary variables of interest, I included a very basic measure to assess motivation and perceived difficulty for each session on a seven point Likert-scale (1 representing no motivation/ finding the session very easy; to 7 representing being very motivated / finding the session very difficult). Furthermore, we asked participants to indicate how concentrated and relaxed they were after each trial on a seven point scale (1 indicating very low concentration or relaxation, 7 indicating high concentration or relaxation). Average scores will be used in the analyses.

2.4 Statistical analyses

The current study is an explorative one, which leads me to focus mainly on descriptive statistics and visual exploration of the data. Descriptive statistics and most graphs were produced in SPSS 17. To explore the data visually, graphs showing amplitude over time (session or trial), per condition, for low, medium and high scores of the individual differences variables. Scores less than one SD below the mean were categorized as ‘low’, scores over one SD above the mean were categorized as ‘high’, and everything in between as ‘medium’. Cognitive style was divided in two: analytic and wholistic, split by the mean.

To answer the first research question, pertaining to general successfulness of the training protocols, an approach for constructing learning indices in NFT recommended by Dempster and Vernon (2009) has been followed. I constructed a measure of amplitude change (in µV) by subtracting each mean raw amplitude value per trial from its corresponding session baseline (active trial – session resting-state baseline). This variable was used as dependent variable in a one-way ANOVA with condition as factor. To assess tonic learning, three (one per condition) one-way ANOVAs on baseline EEG with session as predictor have been conducted. The baseline resting-state amplitude for the second to last session were compared to the first session’s baseline. In addition, a 3 (condition) x 8 (session) x 8 (trial) repeated-measures factorial ANOVA has been applied to analyse the change in average active amplitude over sessions. After finding the assumption of sphericity violated, I used Greenhouse-Geisser corrected F-statistics in all analyses. Analyses were conducted separately for theta amplitude (µV) and beta amplitude as dependent variables. Subsequently, participants were categorized on tonic and phasic learning by computing binary variables (0=no learning, 1=learning) based on the newly constructed change measures. Theta trainers were classified as phasic learners when the average amplitude during a session was lower than the session baseline value, and as tonic learners when the average baseline amplitude on sessions two to eight was lower than the baseline of the first session. Beta trainers were classified as phasic learners if the average amplitude during active trials was above baseline and tonic learners if the average baseline amplitude over sessions was higher than the first baseline. To explore the relationship between phasic and tonic learning, crosstabs were produced and correlation was measured with the phi correlation coefficient.

Given that observations in neurofeedback research are inherently dependent within sessions and participants, a multilevel approach using R has been used to analyse the data further. To answer the last research question, if individual differences predict tonic or phasic learning, a basic model with raw theta or beta amplitude as dependent variables, trials (nested within session) and session as time variables, and condition as predictor or grouping variable was tested. The intercept of session and slopes of both session and trial were included as random factors. In the theta model, trial was included only as fixed factor because allowing random variation for this variable did not contribute to the model (the random effects estimate was near zero). To test whether individual differences affect tonic or phasic NFB efficacy, multiple multilevel models were constructed, every analysis assessing the effect of one of the individual difference variables as a predictor and allowing it to interact with session, trial, and training condition. A full overview of the variables included in the analysis can be found in Appendix A.

2.5 Missing data

As mentioned earlier, psychometric data for two participants of the random feedback condition were missing and removed from the last analyses. Furthermore, seven trials were not saved correctly and treated as missing data in the RM ANOVA's.

3. Results

3.1 Individual differences

The results of the questionnaire-outcomes are summarized in Table 1.

	Random feedback (N=7)		**Theta training (N=10)**		**Beta training (N=9)**	
	Mean	**SD**	**Mean**	**SD**	**Mean**	**SD**
Motivation per session	5.14	1.32	5.39	0.91	5.30	1.01
Perceived session difficulty	4.46	1.17	4.32	1.21	3.97	1.33
CSA-WA	1.10	0.11	1.03	0.14	1.07	0.03
MAAS	54.00	9.93	57.80	10.01	50.33	9.67
Rotter’s Locus of Control	12.34	3.69	12.50	3.69	11.67	3.43
BIS	19.34	2.88	18.94	3.14	20.67	3.94
BAS-drive	14.14	1.95	13.30	2.26	13.33	3.00
BAS-fun seeking	12.57	2.44	12.20	2.20	11.89	2.26
BAS-reward responsiveness	14.57	1.51	15.20	1.32	16.22	1.30
SPQ – deep	28.86	4.88	31.00	7.96	25.56	8.58
SPQ – surface	22.00	5.94	20.10	4.79	22.67	3.91
Extroversion	33.00	6.66	35.90	5.63	31.11	7.42
Agreeableness	38.43	5.16	39.00	4.96	37.22	6.36
Conscientiousness	33.00	6.30	29.40	5.13	30.11	4.43
Intelligence/imaginative	36.61	3.05	37.20	5.11	35.22	5.87
Emotional stability	26.29	8.64	29.90	8.06	26.33	7.25

Table 1. *Overview of mean and standard deviations of the psychometric assessments per training condition.*

Descriptive statistics on the individual differences measures were compared between the three conditions and tested for significance using one-way ANOVAs. None of the group differences were significant. Mean scores on Rotter’s test of Locus of Control were equal in all three groups. There was a small difference in CSA-WA ratio between the beta and theta training groups, with a bias towards analytic processing in the beta group. The variance in our sample was low, which suggests that few of our participants had a clear cognitive preference. Only four participants in the theta group and three participants in the random feedback group showed a preference for a wholistic cognitive style. The mean scores on SPQ deep motive and strategy are lower in the beta group, whereas SPQ surface scores were slightly lower in the theta group. Mean scores on BIS, BAS Drive, Reward Responsiveness and Fun Seeking items were approximately equal across groups. With respect to the personality questionnaires, no significant group differences were found either. Emotional stability scores were somewhat higher in the theta group compared to the other groups and scores on conscientiousness items were on average slightly higher in the random feedback group.

In addition, possible changes in motivation and perceived difficulty were inspected over time. Motivation decreased over time in the random feedback group, with occasional peaks. In the theta and beta training groups, the relationship takes on an inverted-U shape with a sudden increase for the last session. Perceived difficulty decreased over sessions in the beta training group, in the theta group we can see an initial increase but lower values as of the fifth session (see Figure 2).

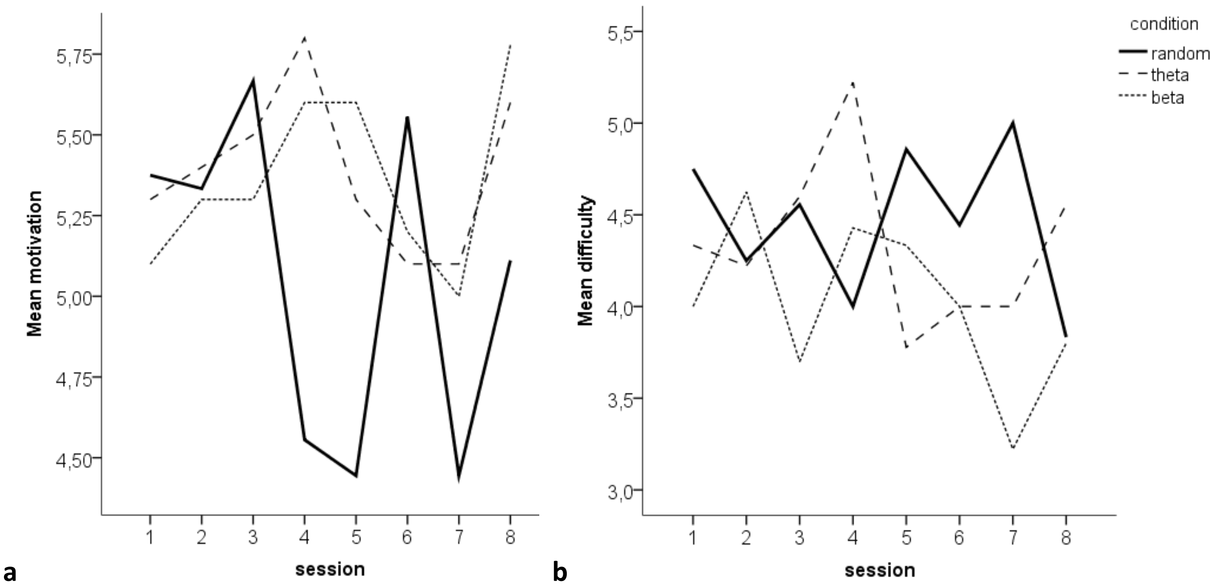

Figure 2. *Line graph of the development of motivation (a) and perceived session difficulty (b) over sessions for the three training conditions.*

3.2 Research question 1: Did participants learn to manipulate the intended EEG frequency and were lasting effects achieved?

3.2.1 Phasic learning

3.2.1.a One-way ANOVA. An average for absolute change in amplitude during trials was computed by correcting raw amplitude trial data for baseline amplitude per session (active trial – session resting-state baseline) and collapsing the values within sessions. The resulting variable 'average active trial' served as dependent variable in a one-way ANOVA, with *condition* as factor. There was no main effect of *condition* on average theta amplitude change (Welch' *F*(2,146) = 1.39, *p*=.25), nor on average beta amplitude change (*F*(2, 229)=.25, *p*=.78). Neither theta nor beta training showed training specific effects with respect to this collapsed measure of within-session amplitude change. Plotting the average change in amplitude (Figure 3) revealed that there were indeed many participants who failed to inhibit theta or enhance beta when training.

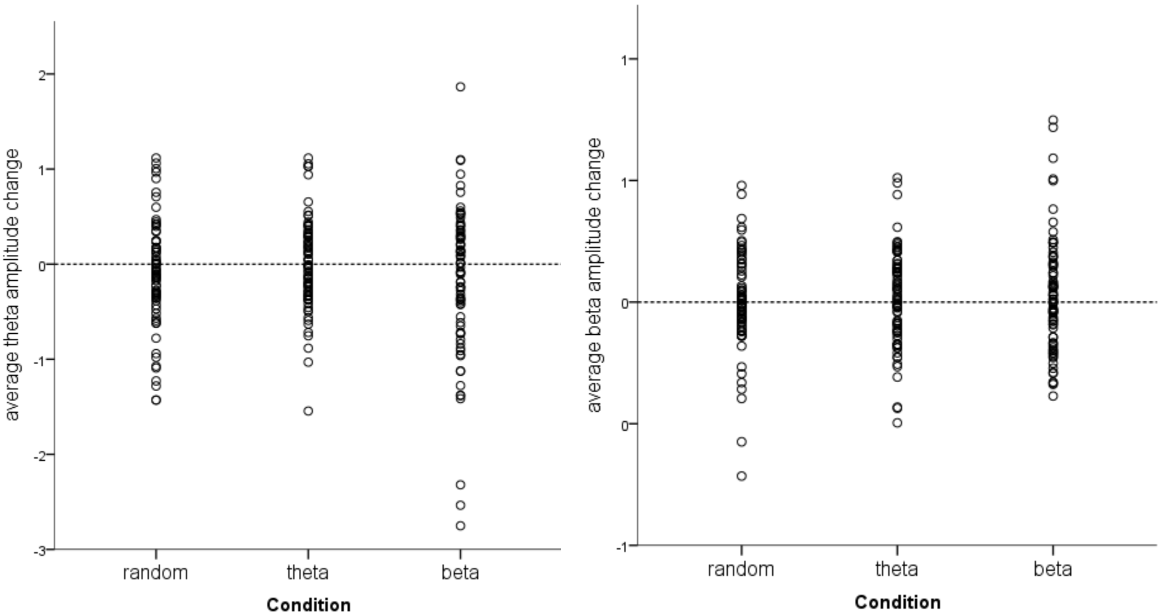

Figure 3.
Scatterplots of the distribution of theta and beta amplitude change (active training – baseline, averaged over trials and sessions) by training condition. Regarding theta amplitude change, values below 0 are in the targeted direction, for beta amplitude change these should be above 0.

However, because the interest of this study did not lie with the specificity of a training condition, a binary variable was constructed to indicate if a participant was successful in actively manipulating the targeted frequency in the right direction in relation to the sessions baseline amplitude (number of trials during amplitude was raised or inhibited compared to session baseline ≥ 4). This is a less strict index than taking the average and provides information on whether or not learning occurred, without taking the size of the change into account. Table 2 provides an overview. In both groups, over half of the participants achieved phasic learning.

			Phasic Learning		
Condition			**No**	**Yes**	**total**
Theta	Tonic learning	no	0	3	3
		yes	3	4	7
	Total		*3*	*7*	*10*
Beta	Tonic learning	no	3	3	6
		yes	1	3	4
	Total		*4*	*6*	*10*

Table 2. *Crosstab of tonic and phasic learners within the theta and beta training groups. The difference between the beta and theta training groups in phasic ($\chi^2(1)=.22, p=.64$) or tonic learning ($\chi^2(1)=1.82, p=.19$) is not significant.*

3.2.1.b RM mixed factorial ANOVA. A 3 (condition) x 8 (trial) x 8 (session) mixed factorial repeated measures ANOVA on theta amplitude corrected for baseline showed a significant main effect of *trial* ($F(4,84)=15.87$, $p<.01$, $\eta^2=.43$). Plots and pairwise comparisons, testing the eight levels of trials against one another, revealed that theta amplitude decreased over trials. The interaction effects of *trial* and *condition* ($F(8,84)=1.72$, $p=.07$) and *trial*, *session*, and *condition* were near significant ($F(21,219)=1.36$, $p=.06$). Plotting the relationship (Figure 4a) shows that theta inhibition within sessions was not specific to the theta training group, although participants seemed to inhibit theta more consistently and stronger in the later sessions. No significant effects were found on raw beta amplitude (Figure 4b).

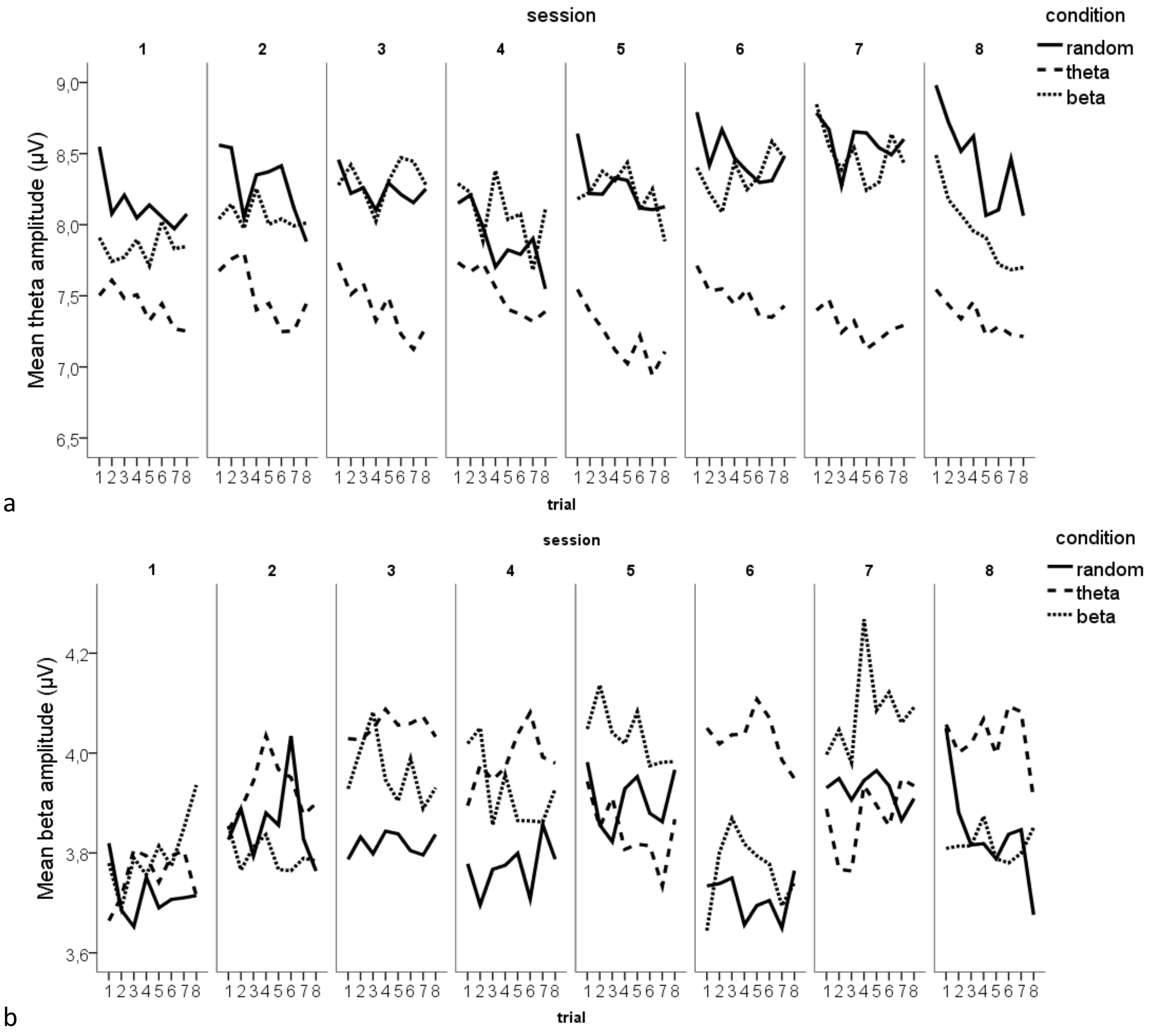

Figure 4.
Overview of theta amplitude (a) and beta amplitude (b) change over trials and sessions with different lines representing the three training conditions.

3.2.2 Tonic learning

3.2.2.a One-way ANOVA. The analyses of average baseline amplitude revealed a main effect of *condition* on theta baseline amplitude (Welch's *F*(2,151)=8.48, *p*<.01) but not on beta amplitude (Welch's *F*(2,150)=.39, *p*=.68). Post-hoc comparisons between groups show the difference in theta amplitude results from a lower amplitude in the theta training group (Figure 5).

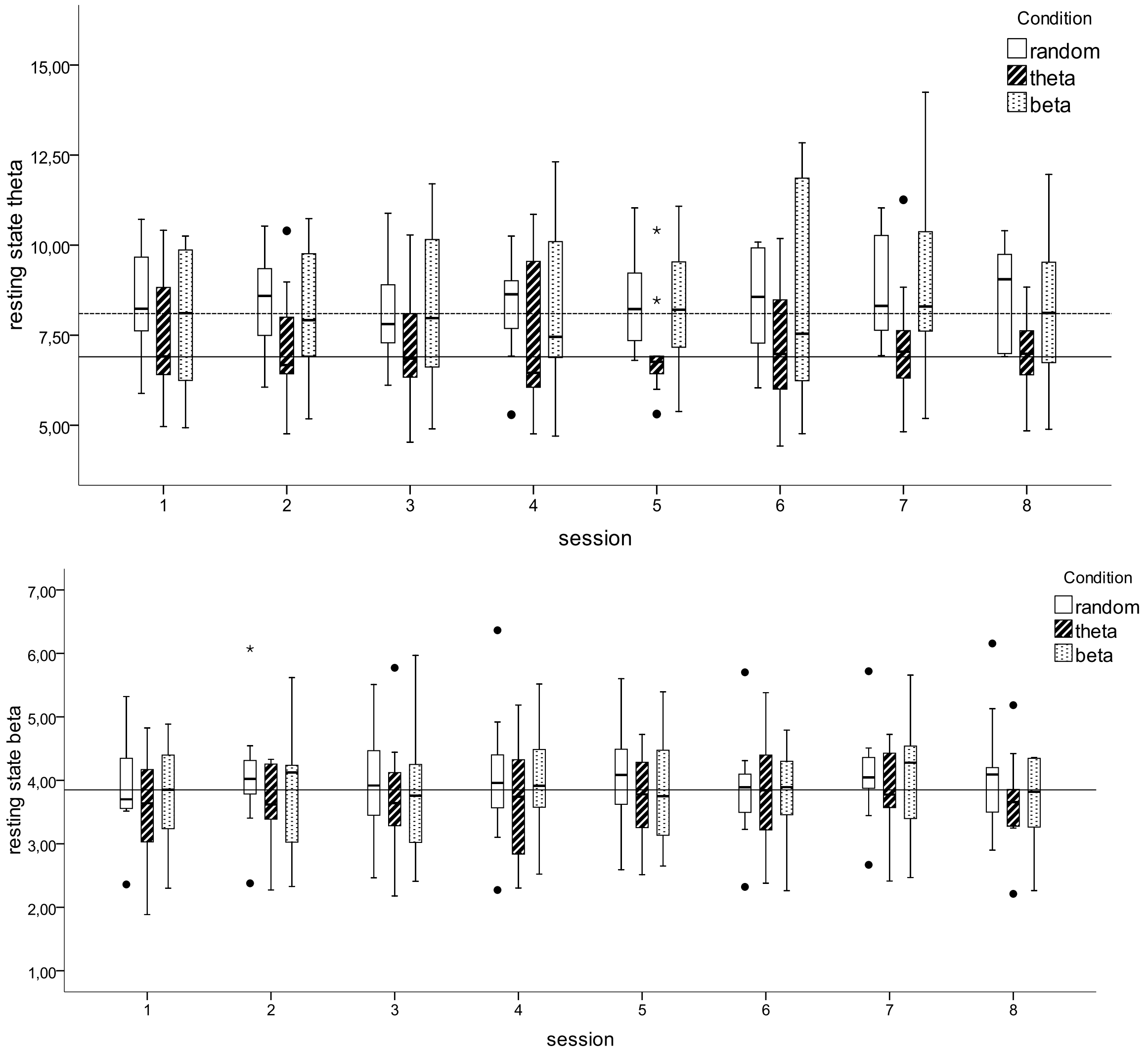

Figure 5.
Box-and-whiskers plots of raw theta and beta amplitude over sessions by training condition. The horizontal dotted line represents the average of the beta and random feedback conditions, the continuous line represents the average in the theta group. Dots represent outlying scores, asterisks denote outliers over three SD from the mean.

3.2.2.b Repeated measures factorial ANOVA. The repeated measures analyses yielded no significant main effect of *session* (*F*(5,96)=1.04, *p*=.41), nor an interaction with *condition* (*F*(9,96)= 1.38, *p*=.21) on theta amplitude. This indicates that the average raw theta amplitude during active training did not change significantly over sessions. However, Figure 4a shows that the theta group consistently maintained lower theta amplitude over sessions, as expected when training would be effective. Theta amplitude increased over sessions in the other two groups. Regarding beta amplitude, no significant effects were found although beta and random feedback participants seemed to have higher beta levels compared to theta trainers (corresponding to the near significant interaction between *session* and *condition, F*(9,95)=1.70, *p*=.06).

3.2.3 Section summary

We can see that in both training conditions, about two-thirds of the participants managed to actively manipulate the intended EEG frequency phasic learning. Phasic learning did occur but not specific to training protocols. Only with respect to theta amplitude the effect seemed slightly larger in the theta training group than in the other two groups, but it did not reach significance.

Evidence for tonic change was found in the theta training group, where theta amplitude remained low over sessions compared to the other two groups, although the finding was not statistically significant. Our data do not support a decrease in amplitude over sessions. There appeared to be an increase in beta amplitude over sessions in both the beta and random feedback groups, but again the effect was very small.

3.3 Research question 2: Does successful manipulation of the targeted EEG frequency predict lasting change in resting-state EEG over sessions?

Similar to the phasic learning variable, a binary variable was constructed to indicate tonic learning. Bivariate two-sided correlation analysis between the newly constructed tonic and phasic learning variables failed to yield significant correlations in both the theta (*phi*=-.43, *p*=.18) and beta groups (*phi*=.25, *p*=.43). There were four participants in the theta group and four participants in the beta group who could successfully manipulate their EEG during training but did not achieve lasting change (Table 2).

3.4 Research question 3: Do individual differences correlate with beta and theta amplitude?

Before covering amplitude development over time, I will briefly discuss the findings pertaining to the main effects of individual differences on raw theta and beta amplitude. The statistical approach is explained in the context of the fourth research question later in this paper.

3.4.1. Main effects on theta amplitude

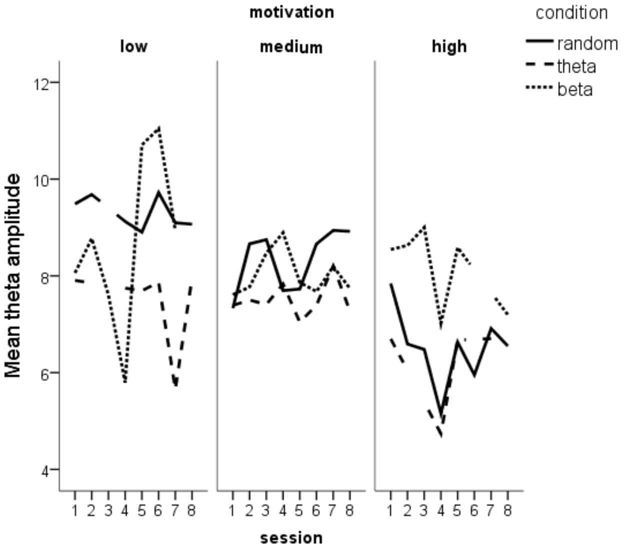

Figure 6. *Line graph depicting the relationship between motivation and theta amplitude over sessions.*

We found that two of our thirteen individual difference measurements had a significant negative relationship with theta amplitude: *mindfulness* (*b*=-1.53, *t*(20)=-2.71, *p*<.05) and *SPQ deep learning* (*b*=-.26, *t*(20)=-2.24, *p*<.05). Two other individual differences showed a positive relationship with theta amplitude: *behavioural inhibition* (*b*=4.52, *t*(1683)=2.35, *p*<.05) and *SPQ surface learning* (*b*=1.62, *t*(22)=2.67, *p*<.05). Furthermore, there seemed to be a relationship between *motivation* and theta amplitude (*b*=.40, *t*(1785)=4.34, *p*<.01). Figure 6 shows this relationship. Interestingly, the outcome of the multilevel analysis does not quite correspond to the trends found in these graphs. It appears that, although the estimate was positive, motivation actually was negatively correlated with theta amplitude: the higher motivation, the lower the amplitude.

3.4.2. Main effects on beta amplitude

The only positive significant main effect on beta amplitude was the effect of perceived *session difficulty* (*b*=-.24, *t*(1518)=-3.26, *p*<.01). *Mindfulness* showed a negative relationship with beta amplitude (*b*=-.07, *t*(20)=-2.26, *p*<.05). Furthermore, a preference for wholistic *cognitive processing* *style* seemed to relate to higher beta levels than a preference for analytic processing (see Figure 7b below). This effect almost reached significance (*b=1.09, t*(21)=.55, *p*=.06).

3.5 Research question 4: Is learning predicted by individual differences measures?

To answer this research question, a multilevel modelling approach has been adopted. The model that served as basis for the analysis of individual differences predicted theta and beta amplitude from *session*, *trial*, *condition*[1], and all interaction terms. A justification for the choices on random and fixed effects can be found in Appendix B. Contrary to the outcome of the ANOVAs, *session* was found to be a positive and significant predictor of theta amplitude (*b*=.11, *t*(1810)=2.57, *p*<.05). Furthermore, a significant interaction effect of *condition* (theta versus random feedback) and *session* (*b*=-.12, *t*(1810)=-2.10, *p*<.05) indicated that the increase over sessions was smaller in the theta training group. Theta training thus seems to have been partially successful. The only significant predictor of beta amplitude was *session* (*b*=.08, *t*(1810)=3.50, *p*<.01), indicating that beta amplitude on average increased over sessions in all groups.

Below I will discuss the most important findings pertaining to inter-individual differences. Effects that were significant but less relevant are included in Appendix C.

3.5.1 Phasic learning

3.5.1.a Beta amplitude change. We found that phasic beta amplitude change could be predicted by interactions with locus of control, cognitive style, and perceived difficulty of the session.

Locus of control interacted with *condition* (beta vs control) on within-session beta amplitude change, *b*=-.008, *t*(1620)=-3.01, *p*<.01 (Figure 7a). Participants in the beta training group with scores further from the mean showed higher beta levels. Interestingly, those with an internal locus of control managed to increase beta amplitude within sessions, whereas those with an external locus of control showed an increase in inhibition over time. The interaction of *cognitive style* with *trial* and

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[1] The R multilevel software contrasts each training condition with the control condition. Omnibus tests were not performed because the difference between the two training protocols of interest is not relevant.

condition (beta vs random, *b*=.83, *t*(1681)=3.26, *p*<.01) is displayed in Figure 7b. Beta amplitude enhancement was successful in participants with a preference for an analytic cognitive style, most clearly in the beta training condition. Participants with wholistic styles showed higher beta amplitude levels, but a decrease rather than the intended increase during a session. This effect is clearest in the beta training condition.

The last three-way interaction involves perceived *session difficulty* and *condition* (beta versus control, *b*=-.02, *t*(1515)=-2.39, *p*<.02). Figure 7c shows that although difficulty correlates positively with beta amplitude, beta trainers who perceived the session as difficult did indeed have trouble increasing their beta amplitude during these sessions. Interestingly, perceiving the session as less difficult did not necessarily correspond to better performance.

3.5.1.b Theta amplitude change. No significant interactions were found on phasic theta amplitude change.

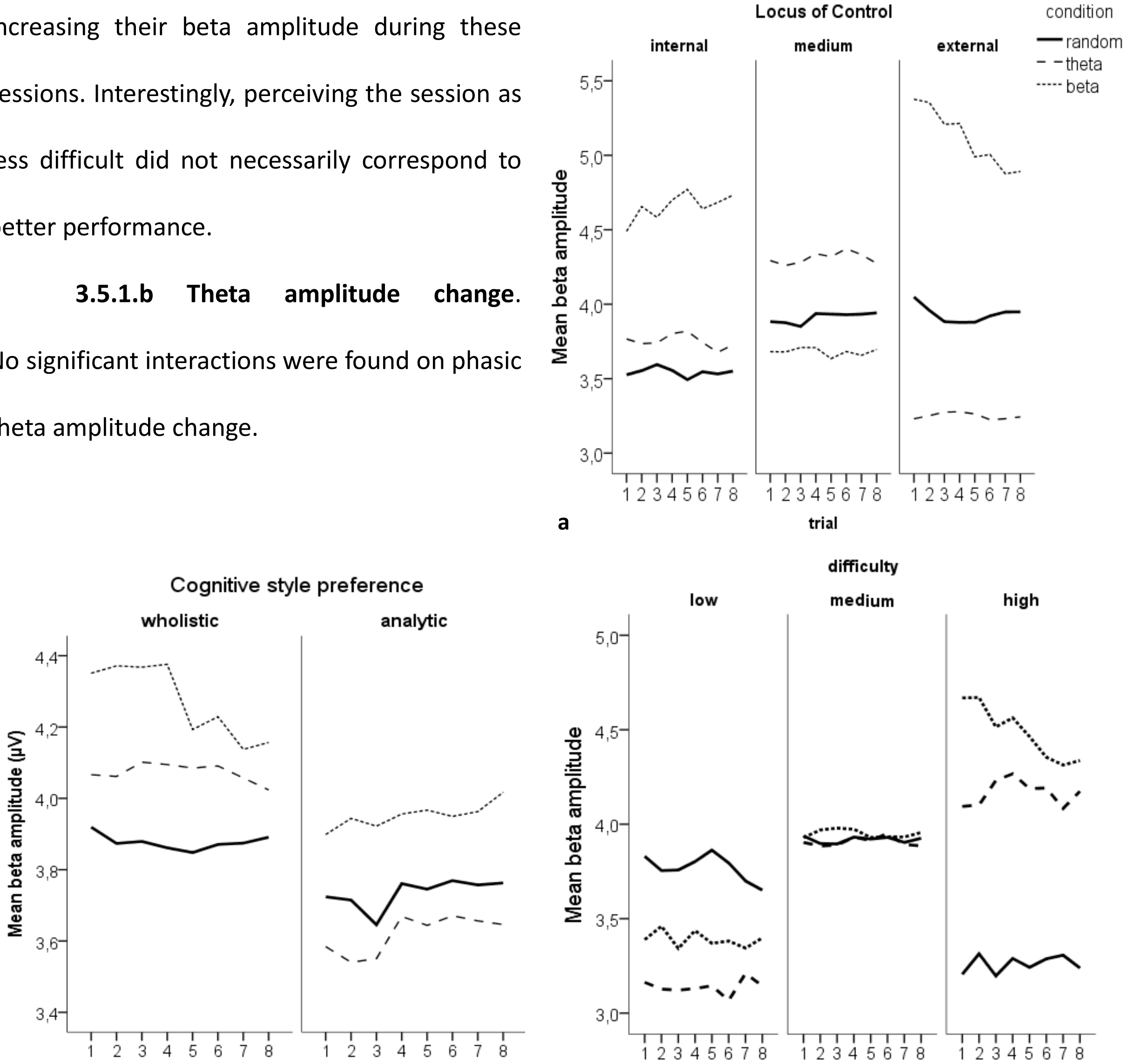

Figure 7. *Line graphs showing the average change of phasic beta amplitude within sessions, for different values of locus of control (a), cognitive style (b), and perceived session difficulty (c).*

3.5.2 Tonic learning

3.5.2.a Beta amplitude change. In our data, significant predictors of tonic beta amplitude change were different from factors predicting phasic change. Interaction effects were found with learning style, motivation, and perceived session difficulty.

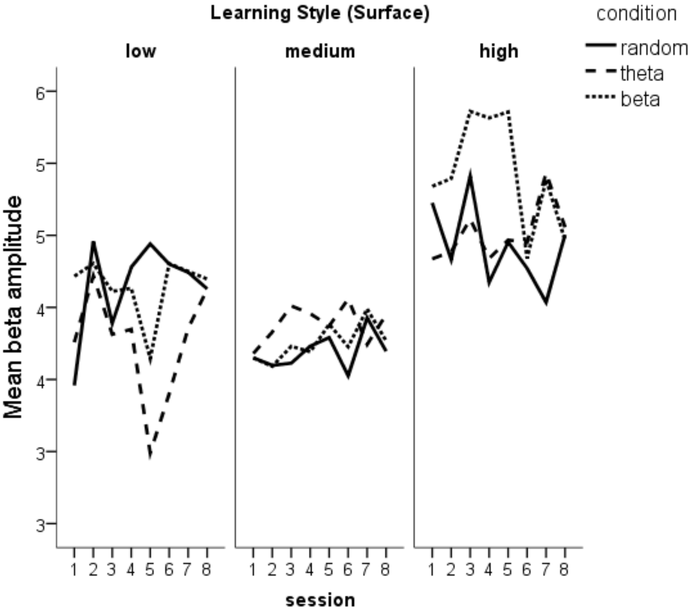

Figure 8. *Line graphs of the relationships between surface learning styles and tonic beta amplitude change.*

SPQ surface scores had a small but significant interaction effect on tonic change, $b=-.005$, $t(1620)=-2.15$, $p<.05$. The three-way interaction with *condition* (beta versus random) was significant as well, $b=.01$, $t(1620)=2.36$, $p<.02$. Especially in the group scoring low on surface learning style, the development of beta amplitude over sessions showed group differences (Figure 8). Beta decreased in the beta training group, whereas it increased in the random feedback participants. The opposite pattern was found in participants with high scores on the surface learning style. Secondly, perceived *session difficulty* interacted with *condition* (beta versus control: $b=.02$, $t(1515)=2.27$, $p<.05$; theta versus control: $b=.02$, $t(1515)=2.39$, $p<.02$). Session difficulty appeared to correlate positively with beta amplitude, showing stronger increases over sessions for low and medium scores (Figure 9a). This finding corresponds to the pattern found for phasic learning, and similar effects were found in the theta training group. Lastly, *motivation* appeared to interact significantly with *condition* (beta versus control, $b=-.03$, $t(1785)=.49$, $p<.02$). Figure 9b depicts this relationship and shows that beta amplitude increased over sessions in highly motivated participants that received beta training, but not in the other training groups.

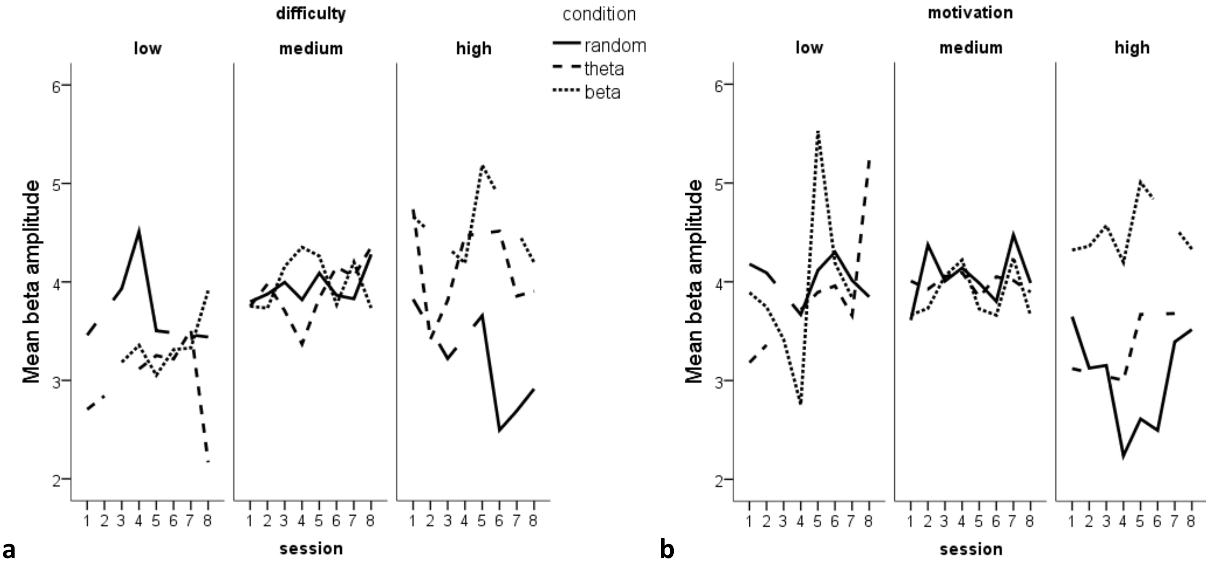

Figure 9. *Line graphs of the relationship between motivation and perceived session difficulty in the context of tonic change in beta amplitude.*

3.5.2.b Theta amplitude change. Although we failed to find significant predictors of phasic theta amplitude change, our data revealed several predictors of tonic theta change: mindfulness, reward responsiveness, fun seeking, motivation, and perceived difficulty.

Worth noting is the near significant interaction effect of *mindfulness* (theta vs random; *b*=-2.87, *t*(1623)=-.64, *p*=.052). In Figure 10a we see that theta amplitude was lower and decreased over sessions for theta training participants with low mindfulness scores, compared to the other two groups. *Fun seeking* (BAS) significantly interacted with *condition* (theta versus random, *b*=-5.89, *t*(1681)=-3.00, *p*<.01). In the theta training group, fun seeking had a positive relationship with theta amplitude, whereby those with high fun seeking scores most effectively inhibited theta (Figure 10b). In the random feedback group, theta amplitude was much lower for high fun seeking scores, but increased over sessions.

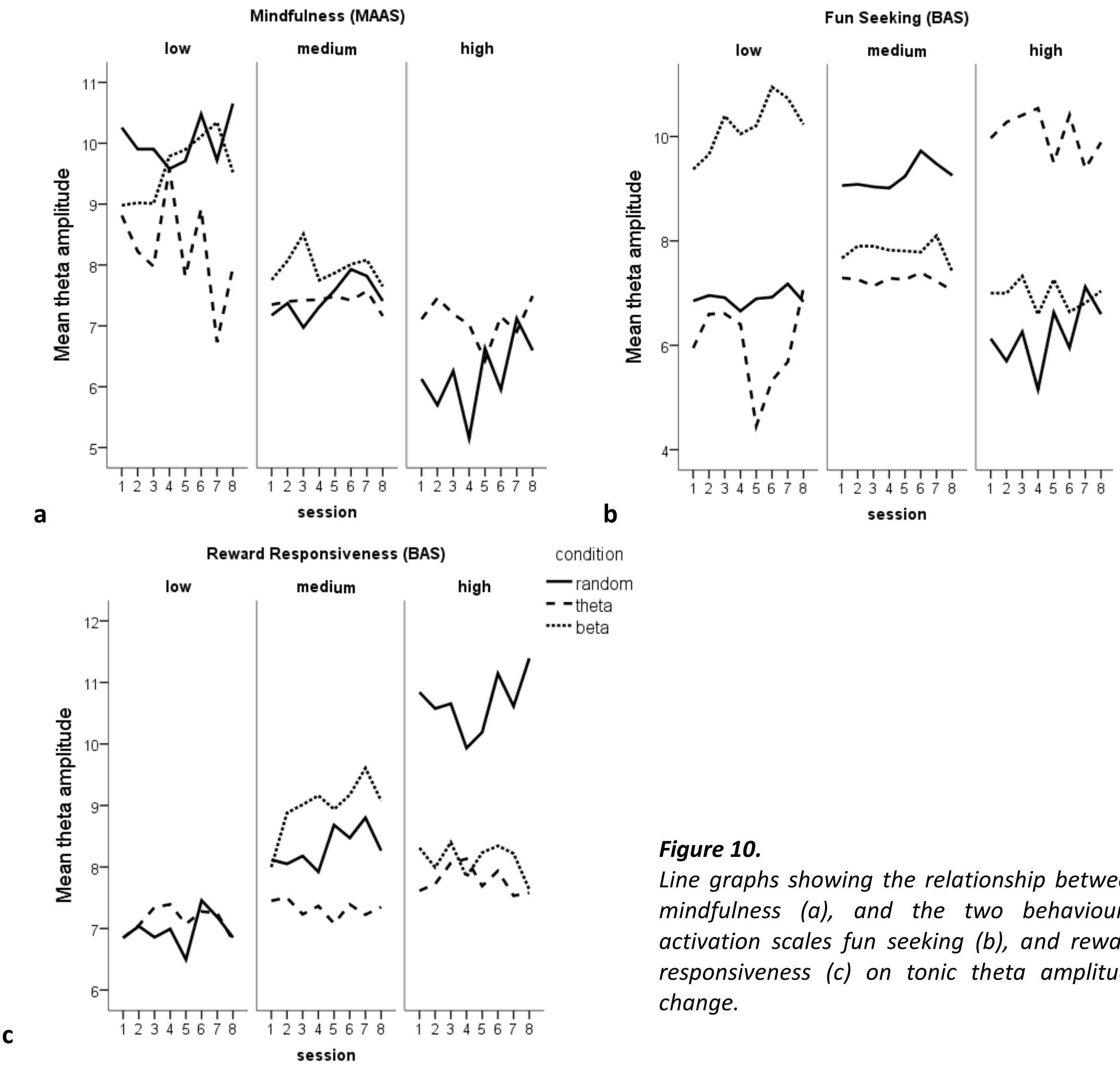

Figure 10.
Line graphs showing the relationship between mindfulness (a), and the two behavioural activation scales fun seeking (b), and reward responsiveness (c) on tonic theta amplitude change.

The interaction effect of *reward responsiveness* (*b*=-8.14, *t*(1681)=-2.34, *p*<.05) represented a positive correlation between reward responsiveness and theta amplitude change over sessions, which was present in the random feedback group but not in the theta inhibition group. Theta trainers managed to maintain low levels of theta and inhibit over sessions relatively independent of score on reward responsiveness (see Figure 10c). Interaction effects with *motivation* (*b*=-.008, *t*(1785)=-5.14, *p*<.01), and *motivation* and *condition* (theta vs control, *b*=.12, *t*(1785)=5.47, *p*<.01; see Figure 11a) revealed that highly motivated participants showed lower average theta levels which initially decreased over sessions, followed by an increase in the last four sessions. Theta participants with less motivation did not show this initial inhibition. Similar to the pattern found in phasic learning, *perceived difficulty* interacted with *condition* (theta vs control, *b*=.22, *t*(1518)=2.21, *p*<.05). Figure 11b shows that this effect is unfortunately far less informative than the effect on beta amplitude.

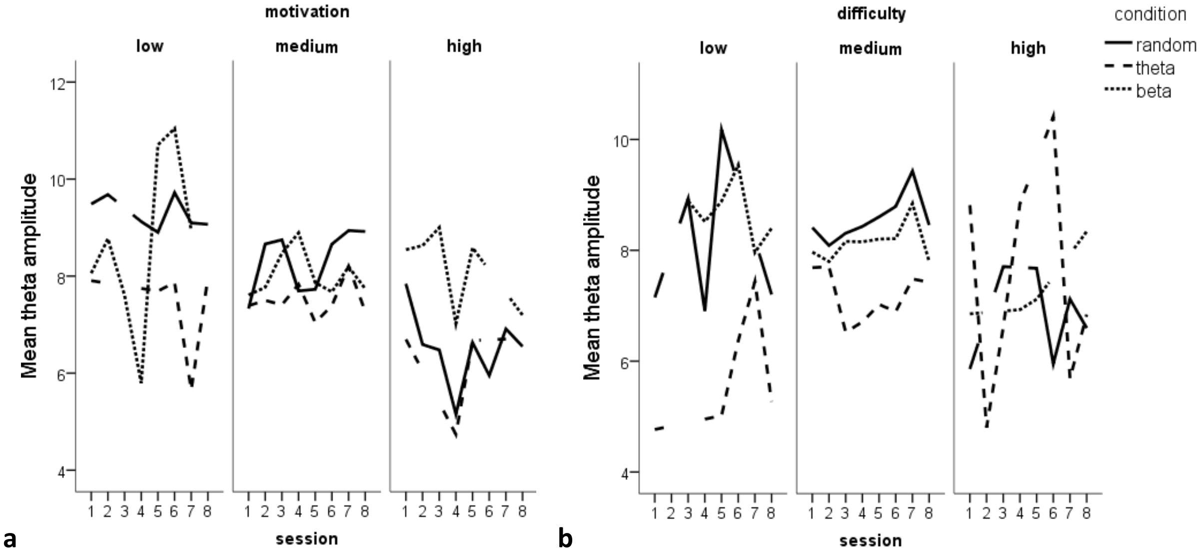

***Figure 11**: Line graphs of the relationship between motivation (a) and perceived session difficulty (b) and tonic change in theta amplitude.*

3.5.2.c Section summary

We found a number of main and interaction effects of our individual difference measures with theta or beta amplitude and amplitude change. Our data suggested a role for learning style, mindfulness, and certain aspects of reward sensitivity and response in lasting effects of neurofeedback training. Our analyses indicated that factors such as locus of control, reward responsiveness, and cognitive style affect the ability to manipulate EEG during the training sessions. Interestingly, motivation only showed up as a significant predictor of lasting change. We found that perceived session difficulty affects the strength of beta synchronization in general, but also the ability to manipulate beta during sessions or to achieve lasting change. Regarding the main effects that emerged, mindfulness seemed to correlate negatively with both theta and beta synchronization. The correlation with difficulty and cognitive style was specific to beta (de)synchronization, whereas the correlations with learning style, behavioural inhibition, and motivation were specific to theta (de)synchronization. Furthermore, the interaction effect of reward responsiveness on tonic theta change seems in fact to represent a positive correlation of reward responsiveness and theta amplitude, which simply did not interfere with theta training. Four of the five personality characteristics (conscientiousness, agreeableness, intelligence/ imaginative, and extroversion) and behavioural drive failed to show significant main or interaction effects in relation to either theta or beta amplitude.

4. Discussion

4.1 Interpretation of the results

The aim of the study was to explore the relationship between learning to manipulate one's EEG through neurofeedback training and individual differences in personality and cognitive characteristics. Furthermore, I explored if we can dissociate participants who are able to learn to manipulate their EEG during neurofeedback training, from those who achieve EEG change lasting over sessions. To this end, 30 students received neurofeedback training to inhibit theta amplitude, enhance beta amplitude, or target a random frequency as control condition. Individual difference factors were derived from psychometric questionnaires and a cognitive style test. The data was visually inspected and tested with several statistical approaches such as ANOVA and multilevel analysis.

4.1.1 Successfulness of the NFT protocols. To be able to make any statements on the learning process itself, I first established if participants managed to manipulate their EEG. We would expect significant interaction effects of condition and trial or condition and session if training was specific to the target frequency. Significant main effects of session or trial indicate non-specific effects of NFT. Unfortunately outcomes of the statistical tests are susceptible to bias due to the small sample sizes, and I conducted careful visual inspection to back-up any (lack of) statistical outcomes.

4.1.1.a Theta protocol. Our results partially support theta training successfulness. We did not find a clear tonic decrease in amplitude over sessions, but as a group, theta training participants managed to inhibit theta amplitude within sessions successfully. Compared to the other two groups, average amplitude remained low. We should note that the basic model constructed by adopting a multilevel approach yielded slightly different results than the RM ANOVA test. Given that this test is more sensitive to the inherent dependency within the data and constructs the estimates with more degrees of freedom, we argue that the multilevel results are more reliable. The interpretation does not change, but we may assume that there was a statistically significant change over sessions.

Contrary to tonic change, phasic effects seemed not specific to the training, as theta amplitude decreased in all three groups, with increasing strength in the beta training group. The major question is if a within-session decrease in theta can be explained by the mere fact that participants actively engage in neurofeedback training and adapt to the task (Gruzelier, 2014). Theta frequency is generally assumed to correlate with basic aspects of cognitive processing such as attentional orienting, action monitoring, and working memory (Basar et al., 2001; Vernon et al., 2003) and these are clearly cognitive processes that one draws upon when engaging in NFT. The underlying mechanisms need yet to be explored and are beyond the scope of this paper.

4.1.1.b Beta protocol. It was harder to find support for the efficacy of the beta training protocol. Although we found significant increases in beta amplitude over sessions which supports tonic EEG change (except for the last three sessions), the differences between groups were only near significant. Furthermore, we could not find a consistent pattern in the development of beta amplitude for any of the three groups, as the interindividual variability proved large. Considering phasic change, we see that the beta trainers on average inhibited amplitude within most sessions, rather than increased. The theta training group shows a similar but slightly less extreme pattern, whereby theta trainers actually seem to increase beta levels within sessions more than the beta trainers. The failure to demonstrate learning in a beta training protocol is not specific to this study (see Egner & Gruzelier, 2001; Vernon, 2005). Unfortunately it makes the interpretation of our main research questions more difficult.

I will not argue against the hypothesis that NFT affects specific frequency bands, but our results are more in line with the notion that the brain is too complex to assume independency of EEG frequencies. We should not be surprised that specific NFT protocols have more generic effects. Especially theta and beta are often mentioned in relation to one another, which was one of the reasons why both protocols were employed in this study. Elevated theta and lower beta levels are found in people with attention deficit disorders and that combined theta/beta protocols are effective in treating disorders such as AD/HD (Gruzelier & Egner, 2005). Our results suggest that targeting either one of the frequencies automatically triggers change in the other frequency without actively monitoring for it. Given that we did not include post-training assessments of attention in this paper, we cannot draw any conclusions on the effect of the single frequency protocol on the full EEG spectrum, but we may well find generic changes in other frequency bands.

Phasic changes in beta activity, which we found in all groups, may be seen as support for the hypothesis that beta is the physiological correlate of attentional processing (Gruzelier & Egner, 2005) or represents inhibition of distracting processes to allow better attention (Vachon-Presseau, Achim & Benoit-Lajoie, 2009). In that case, we would expect elevated beta levels simply due to the fact that participants are attending (or facilitating attentional processes) to the visual representation of their brain waves on the computer screen. This would argue for nonspecificity of training, as found in several other neurofeedback studies (Gruzelier, 2014). The theory is however not fully supported by our data, because beta levels in the random feedback group were lower than in the other two groups.

4.1.1.c The relationship between phasic and tonic change. We further inspected the data at the level of each individual to see if participants that can manipulate their EEG in the right direction during training (phasic change), also achieve lasting (tonic) EEG change. About half of the participants achieved either tonic or phasic change, four participants failed to learn at all, and six achieved both. From this we can conclude that phasic learning does not necessarily predict or precede lasting EEG change. However, evidence for a clear dissociation has not been found.

4.1.2 Influence of individual differences. The primary aim of this study was to see if individual differences in personality and cognitive characteristics affect the change in amplitude over time. We found several interaction effects of individual differences with time on theta and beta amplitude, and alongside a number of main effects of these individual differences measures on theta and beta amplitude in general.

4.1.2.a Main effects. Mindfulness, an analytic cognitive style, and perceiving the session as more difficult correlated with lower beta amplitude. When looking at the visual representation of the relationship with session difficulty (see 7d, 9b), we can see that this negative relationship might be biased. In fact, the trend seems positive, but due to low beta scores in a few influential random feedback participants that perceived the session as difficult, the estimate turns out negative. Nonetheless, if enhanced beta correlates with better attentional processing, the finding makes sense. We cannot draw any conclusions on the direction of the effect, but we can speculate that low beta manifests to the individual as higher (perceived) difficulty to attend to the task at hand. As perceived difficulty decreased over sessions in the beta training group, this might correspond to effectiveness of the training in improving this effect.

In relation to the theta frequency band, we found that mindfulness, motivation, and a preference for a deep learning style correlated negatively with theta amplitude, whereas behavioural inhibition and a preference for surface learning were associated with higher theta amplitude. The findings on mindfulness and motivation are worth exploring a little further. Konareva (2009) studied the relationship between motivation as personality characteristic and evidence for theta synchronization to be an EEG correlate of achievement motivation. Visually inspecting our data, theta appears negatively correlated with motivation. Our measure does not assess motivation as a personality trait and is much less sensitive and more subjective than that of Konareva, which might explain the difference. Instead, our measure is similar to that of a study on the psychophysiological correlates of positive emotion and motivation (Rusalova & Kostyunina, 2003). Their research revealed inverse correlations between theta and motivation in various brain regions, corresponding to our findings.

Mindfulness has previously been associated with increased theta and beta levels (Dunn, Hartigan & Mikulas, 1999; Ivanovski & Malhi, 2007), which is contrary to the outcomes from our data. Perhaps this is due to mindfulness being conceptualized in a more superficial manner in our study, compared to studies that have analysed psychophysiology in relation to actual training in meditation and mindfulness. It could be that participants scoring high on the MAAS somehow benefit from enhanced ability to focus and inhibit distracting impulses, but do not show increased theta in the long run, as is suggested typical for more expert practitioners of mindfulness meditation (Tanaka et al., 2014). However, it is also conceivable that due to the small sample size and lack of high mindfulness scores in amongst beta trainers, our data is biased and provides an inaccurate representation of the actual relationship.

4.1.2.b Phasic change. Although we failed to find significant predictors of phasic theta amplitude change, we found four factors to interact with beta amplitude change. Participants with a preference for an analytic cognitive processing style were more likely to raise their amplitude than those with a more wholistic style, although baseline values were higher in the wholistic group. The results are in line with our expectations, building on the theory that analytic people benefit in learning contexts where they have to rely on only a few loose instructions, whereas wholistic participants need more guidance (Riding & Watts, 1997) and might be struggling to figure out what to do in the NFT context. A very similar pattern is found with locus of control: participants with an internal locus of control successfully enhance beta amplitude within sessions, whereas those with an external locus of control show higher beta levels at baseline, but decreasing within sessions. The findings correspond to findings in BCI research (Burde & Blankertz, 2006) and our suggestion that people who believe they have some extent of control over events that happen to them, may find it easier to believe they can manipulate their own brain activity. Such positive expectations may lead to increased motivation, effort, or confidence, with beneficial effects on NFT (Glannon, 2014). This is however a very speculative theory that should be explored further before drawing conclusions. Nijboer and colleagues (2008), for instance, suggested that persistent effort and motivation is required for SMR desynchronization (which partly overlaps with our beta range), whereas it might hamper the relaxed state of mind necessary for synchronization in BCI. This argues against mediation by motivation. Since we assessed motivation only at the start of the session, we lack information on the change of motivation as a result of perceived progress in NFT. Furthermore, we failed to find significant relationships with mindfulness on phasic change. We hypothesized that people who are aware of their own mental state would find it easier to manipulate that mental state during training. Our results fail to provide evidence in that direction.

On a different note, our findings on the relationship between beta amplitude and session difficulty are worth exploring further. Given that high perceived difficulty correlates with high baseline beta, it might be that participants with high beta levels have reached a maximum amplitude which is hard to enhance even further. Gruzelier (2014) mentions in his review that learning curves may be typically characterised by cumulative improvements until a plateau is reached. Such a plateau can be found in within-session manipulation as well as tonic change. As mentioned earlier, the effects of emotional stability and reward responsiveness are difficult to interpret due to the absence of lower scores in the beta training group. Given our small sample size we should not be too surprised that the scores are not always evenly distributed. It is important to conduct follow up studies with larger sample sizes.

4.1.2.c Tonic change. With the exception of perceived difficulty, tonic theta and beta change was predicted by different factors than phasic change. Predictors vary per training protocol. One of the factors correlated with beta training was learning style. Interestingly, high beta amplitude with successive increases over the first half of the sessions were characteristic for high surface learners as well as high deep learners. Assuming that deep and surface scores are considered opposite ends of a scale, it is slightly surprising that the direction the effects take on beta amplitude are similar for both measures. It might be that the neurofeedback context is simply too different from the classroom context that the questionnaire aims at. Another explanation could be that the practical implications of assigning participants learning styles is limited. Some authors in the field (Pashler et al. 2009) argue against such classification. In their study investigating the interaction between supposed learning style and instruction method they found little support for the idea that people learn better in a different context than someone else would. On the other hand, the concepts described by Pashler and colleagues (2009) resemble our notion of cognitive style more than the SPQ learning styles, which indeed failed to show a significant relationships with tonic theta or beta change.

Motivation is a second factor in both beta and theta training success. As mentioned above, previous studies have also found an inverse relationship between theta and motivation, which might facilitate further down-regulation of theta amplitude. Research on a possible relationship between beta and motivation has yet to be conducted, but we may speculate that related mental states such as positive affect play a role. The pattern found in relation to perceived difficulty is somewhat ambiguous. Perceived difficulty seems to have a positive effect on beta amplitude, but the strongest increase is found in relation to low difficulty. However, this reminds one of the plateau-theory discussed under phasic change: if beta is low, it is easier to enhance amplitude than if beta is already higher.

Although we did not find an effect of mindfulness on phasic change, increased mindfulness seemed to facilitate theta inhibition over sessions. An interesting finding is that in our participants, the strongest decrease in theta amplitude is found in the low mindfulness group. Given that the average amplitude in this group was higher than in participants with medium and high mindfulness scores, one might relate this to a minimum amplitude below which it becomes difficult to inhibit further, similar to the beta plateau mentioned earlier. However, the random feedback group reaches even lower levels of theta amplitude without aiming to inhibit this frequency. It would nonetheless be interesting to explore this theory further. Quite opposite to the effect of mindfulness is the relationship with the behavioural activation element ‘fun seeking’. Fun seeking shows a strong positive relationship with theta amplitude, specific to the theta training group. This suggest that fun seeking hampers theta training. People with higher BAS scores are believed to be more susceptible to cues of reward and especially the fun seeking subscale incorporates an element of desire for reward (Carver & White, 1994). Perhaps this higher desire predisposes participants to try too hard, or they may lose interest or become frustrated when rewards are not provided often enough.

The measures of motivation and perceived difficulty do not provide much additional information. We may however tentatively conclude that motivation is important in successfully achieving amplitude change especially in theta training, although the disparity between graphs and statistical outcomes indicate the need for further exploration. It is possible that low theta is a more direct correlate of motivation, as suggested in a study by Rusalova and Kostyunina (2003), or that certain motivational aspects facilitate inhibition but hamper enhancement of EEG frequencies (Nijboer et al., 2008, 2010). On a side note: our data also indicate that participants perceive theta and beta training as about equally difficult, whereas the random feedback group clearly experiences more difficulty and becomes much less motivated over time. Consistency in training protocols seems important for participants' morale.

4.1.3 Overall summary. In short, we can deduce from this exploratory study that neurofeedback learning is affected by inter-individual differences in personality and cognitive characteristics. The result of the interplay between such characteristics and the training environment depend on the operationalization of learning. Learning can be defined as the ability to actively manipulate EEG, or the ability to achieve lasting EEG change. In our study, the first did not necessarily precede the latter, but it is likely that there is a relationship between the two processes that we do not yet understand. We are one step further in elucidating specific characteristics that correlate with these processes. Specifically, having an internal locus of control and a preference for analytic cognitive processing promotes phasic neurofeedback learning, whereas mindfulness, motivation and learning style are factors that facilitate tonic EEG change. Our measures of the big five personality characteristics seem to have little relation to NFT efficacy, which is not too surprising (Hammer et al., 2012). Lastly, in several cases we found a pattern that suggests the existence of a plateau or threshold beyond which it becomes more difficult to further inhibit or enhance a certain frequency.

4.2 Limitations to the study

The results of this study must be interpreted with caution. Given the exploratory nature of the study and the small sample size, statistical results of the multilevel and RM ANOVA approaches may be biased. Careful inspection of the visual representations of the data is required and has been used throughout this thesis to elucidate and verify statistical findings. As mentioned in the results, the variance in individual differences between the three conditions was not equal. Since we did not sample based on any kind of selection, this is not a surprise, but it makes some of the graphs difficult to interpret. In some cases, only a few participants are represented in the low and high categories of the individual differences scales, even though all scores were within two standard deviations of the mean. This also affects visual inspection of the data, as some individual difference categories may actually represent only one or two individuals. Multiple testing had to be performed to explore the effect of individual differences on NFT learning, which enhances the chance of finding an untrue statistically significant result.

Flaws in the study design may have affected the reliability of the study. Examples that are relevant to the present thesis are the lack of randomization and blindness of experimenters. Participants were not randomly assigned to the three conditions, but based on the order in which they had their first appointment. Furthermore, trainers were not blind to the condition and unconscious bias cannot be ruled out, although a protocol for interaction with the participant was set up to keep the bias as low as possible. Limitations to the EEG equipment may have affected the reliability of neurofeedback. For instance, the use of gold electrodes during training, which are considered of less quality than Ag/AgCl electrodes for a number of reasons, is not recommended (Tallgren et al., 2005) and future studies should take care to use the most appropriate equipment available.

4.3 Suggestions for future research

Researchers are recommended to take into account individual differences in cognitive characteristics such as locus of control and cognitive style, when studying neurofeedback efficacy. It would be interesting to see if changing the learning environment by tailoring instructions to the participant, improves performance in participants that are more likely to fail in the current context. Trainers could guide participants with less internal focus and drive, and try to actively keep participants motivated. Furthermore, we found interesting results pertaining to mindfulness and EEG change, which we could not properly elucidate in our design. Studies on the mechanisms underlying mindfulness and meditation may provide an interesting link to neurofeedback, which shares many common characteristics. Further exploration of the role of personality characteristics may prove less fruitful and is therefore not advised.

Follow-up research should either draw upon a larger sample or employ fewer training protocols. Including an active control group that receives the same training save for the use random frequencies, seems to be an appropriate reference to eliminate non-specific training effects. It might prove even more informative to match control group participants on individual differences to further eliminate imbalances that might have biased our results. Despite its limitations, the outcome of this exploratory study is valuable to future studies as it provides useful information on the lines of research that may or may not be pursued.

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Appendix

A. Overview of means and SD's of individual differences measures in each of the three training groups

Variable name	Measured construct	Response characteristics
Theta amplitude	Averaged raw EEG amplitude (6 to 4 Hz below AIF) during 2.5-minute trial.	Continuous
Beta amplitude	Averaged raw EEG amplitude (2 to 5 Hz above AIF) during 2.5-minute trial.	Continuous
Condition	Allocated training condition: random feedback (control), beta enhancement, or theta inhibition. In the multilevel models compares the first with either one of the training conditions.	0 = random feedback 1 = theta 2 = beta training
Baseline	Raw EEG amplitude during resting-state trial (pre-session)	Continuous
Average amplitude change	Average of amplitudes during active trials – resting state baseline of that session	Continuous, centred round 0.
Tonic learning	Indication if targeted frequency was above/below baseline in the majority of sessions measured during resting state baseline.	Binomial: 0 = no 1 = yes
Phasic learning	Indication if targeted frequency was enhanced/inhibited compared to session baseline in the majority of active trials.	Binomial: 0 = no 1 = yes
Motivation	How motivated is the participant for this session? (pre-session)	Ordinal; range 1-7
Difficulty	How difficult did the participant feel the session was? (post-session)	Ordinal; range 1-7
Concentration	How concentrated did the participant feel during the trial?	Ordinal; range 1-7
Relaxation	How relaxed did the participant feel during the trial?	Ordinal; range 1-7
CSA-WA	Preference for cognitive processing style. Values close to 0 reflect a wholistic preference, values close to or above 2 reflect an analytic preference.	Continuous; Range: 0.81 to 1.32.
MAAS	Measures ability to attend non-judgmentally to one's inner state of mind (emotions, thoughts, sensations). High scores reflect high mindfulness. (sum score)	Interval; range 15 to 90
Rotter's LOC	Measures disposition to believe a person has control over events that he experiences (internal locus of control) or attributes it to external factors (external). High scores reflect an external locus of control. (sum score)	Interval; range 0 to 23
BIS	Behavioural inhibition system, sensitive to punishment, non-reward and novelty. High BIS activation is associated with inhibition of movement toward goals, anxiety, frustration. (sum score)	Interval; range 7 to 28
BAS-D	Behavioural activation system, sensitive to reward. High BAS activation is associated with responsiveness to reward, positive affect after reward. The variable represents sum score of Drive items, which pertain to persistence in pursuit of desired goals.	Interval; range 4 to 16
BAS-FS	Sum score of BAS fun seeking items pertain to desire for new rewards.	Interval; range 4 to 16
BAS-RR	Sum score of BAS reward responsiveness items pertain to positive response in anticipating/receiving reward.	Interval; range 5 to 20
SPQ-Deep	Stud Process questionnaire, sum score of 'deep' items. Deep learning generally refers to people who learn to understand the material.	Interval; range 10 to 50

SPQ-Surf	Study Process questionnaire, sum score of ‘surface’ items. Surface learning generally refers to people who learn because they need to reproduce, with minimum effort.	Interval; range 10 to 50
Extroversion	Big Five personality characteristic (sum score)	Interval; range 10 to 50
Agreeableness	Big Five personality characteristic (sum score)	Interval; range 10 to 50
Conscientiousness	Big Five personality characteristic (sum score)	Interval; range 10 to 50
Intelligence/imaginative	Big Five personality characteristic openness to experience (sum score)	Interval; range 10 to 50
Emotional stability	Big Five personality characteristic neuroticism (sum score)	Interval; range 10 to 50

B. Justification of random and fixed effects in the multilevel models.

The relationship between training and theta amplitude showed significant variance in intercepts across participants, *SD*=1.69 (98% CI: 1.23, 2.31), $\chi^2(1)=3402.63$, *p*<.01, and slope of *session* varied significantly across participants, *SD*=.09 (98% CI: .06, .13), $\chi^2(2)=130.15$, *p*<.01. The correlation between intercept and slope was negative but not significant, *r*=-.161 (-.57, .31). The relationship between training and beta amplitude showed significant variance in intercepts across participants, *SD*=.86 (98% CI:.64 , 1.16), $\chi^2(1)=3402.63$, *p*<.01. Slope of session (*SD*=.39 (98% CI: .03, .06), $\chi^2(2)=89.33$, *p*<.01) also varied significantly across participants, and allowing the slope of trial to vary randomly within session and participants significantly improved the model, *SD*=.003 (98% CI: .002, .006), $\chi^2(3)=12.11$, *p*<.01.

C. Significant results not reported in the paper.

Several statistically significant interactions were found on phasic and tonic beta change. Mainly due to a lack of variance in the beta training group, these findings did not provide sufficient information to be included in the paper and are reported below.

Figure 1a displays the relationship of reward responsiveness on phasic beta change. The interaction of *reward responsiveness* and *condition* was significant (beta versus random; *b*=.02, *t*(1681)=2.90, *p*<.01). Figure 2a shows the relationship of *emotional stability* (*b*=-.004, *t*(1620)=-3.46, *p*<.01). The graphs indicate that there were indeed group differences but it is difficult to see how these manifest.

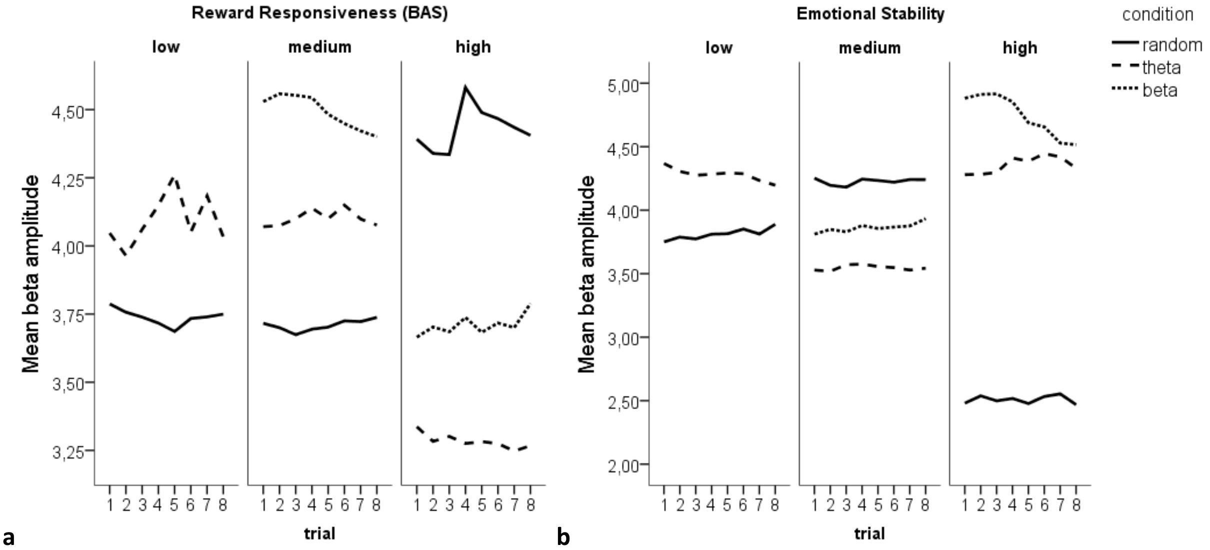

Figure 9*. Line graphs depicting the relationships between reward responsiveness (a) and emotional stability (b) with phasic beta change. Low scores are not represented in the beta training groups.*

Regarding tonic change, a three-way interaction of *SPQ deep* scores with *condition* (theta versus random) and *session* was found (*b*=-.007, *t*(1620)=-2.20, *p*<.05). This resulted mainly from the theta training group behaving differently from the others and does not tell us anything about beta training efficacy (Figure 2a). An effect of *behavioural inhibition* (*b*=-.01, *t*(1678)=-2.40, *p*<.02) seemed to result mainly from group differences in participants that scored low on behavioural inhibition (Figure 2b). The interaction with *mindfulness* and *condition* on tonic beta change was significant (*b*=-.007, *t*(1620)=-4.58, *p*<.01), but does not contribute much to the research question because high scores in the beta training group were lacking (see Figure 2c).

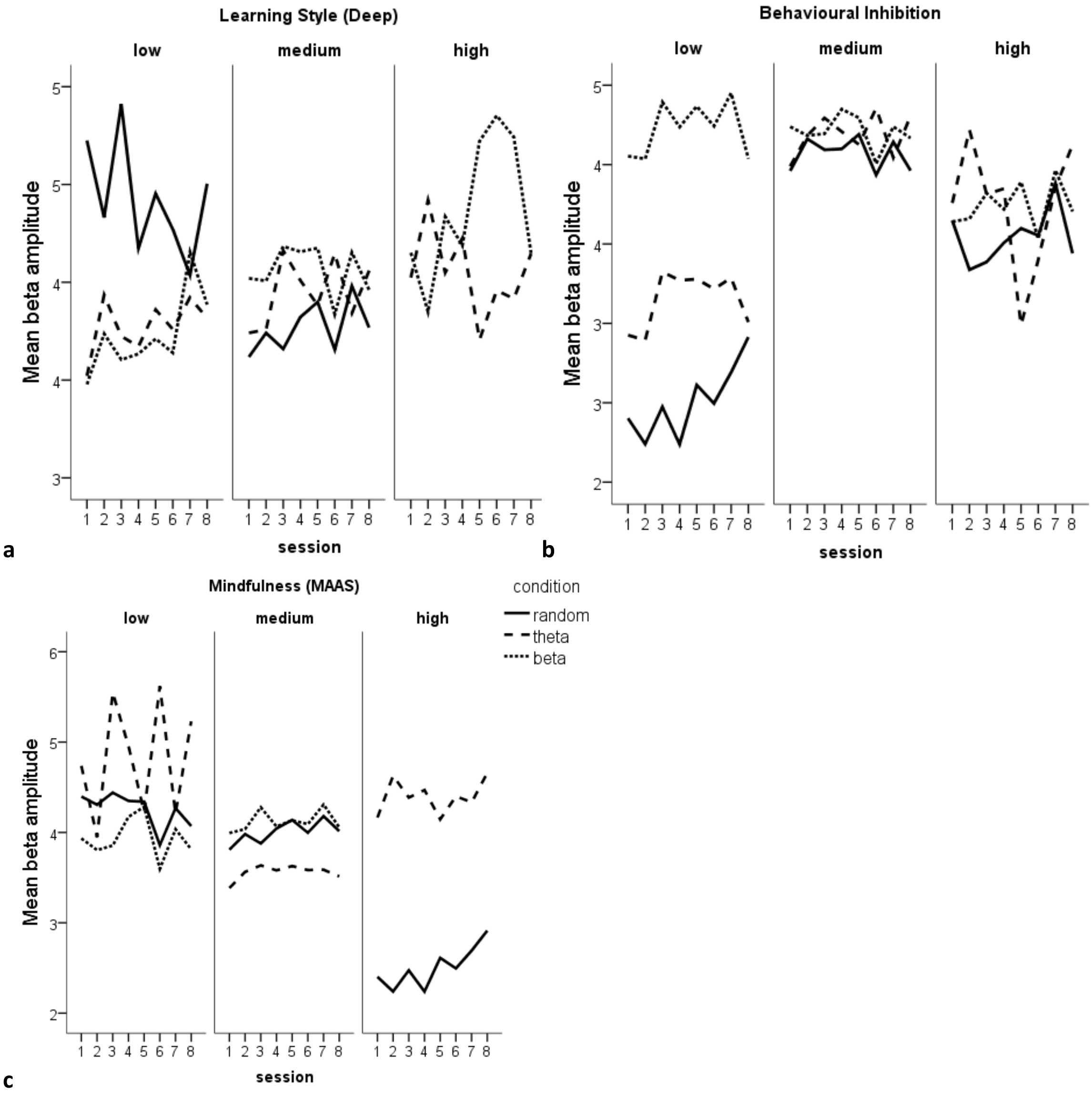

Figure 10. *Line graphs depicting the relationships between deep learning style (a), behavioural inhibition (b), and mindfulness (c) with tonic beta change. High scores are not represented in the beta training group (a and c).*